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How do Insiders Trade?

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How do Insiders Trade in the Options Market?

Abstract

We characterize *how* informed investors trade in the options market ahead of corporate news when they receive private, but noisy, information about (i) the timing of the announcement and (ii) its impact on stock prices. Our theoretical framework generates a rich set of predictions about the insiders' behavior and their maximum expected returns. Three different analyses offer empirical support for our approach. First, predicted trades resemble illegal insider trades documented in SEC litigation cases with insiders being more likely to trade in options that offer higher expected returns. Second, pre-announcement patterns in unusual activity in the options market ahead of significant corporate news are consistent with the predictions of our framework. We employ our approach to characterize informed trading ahead of twelve different types of news including the announcement of earnings, corporate guidance, M&As, product innovations, management changes, and analyst recommendations. Third, to address concerns that pre-announcement patterns are driven by speculation, we show that measures capturing trading activity in call (put) options with high expected returns *predict* significant positive (negative) corporate news in the aggregate cross-section.

Key words: Insider Trading, Market Microstructure, Corporate Announcements, Extreme Price Movements, Equity Options
JEL classification: G12, G13, G14, K42

1. Introduction

According to Preet Bharara, the U.S. Attorney for the Southern District of New York, insider trading is "rampant."[1] Accordingly, the SEC has made it a key priority to prosecute illegal insider trading, and has increased the number of enforcement actions in recent years.[2] Given the importance of illegal insider trading for regulators and policy makers, recent studies have focused on identifying the prevalence of informed trading in the stock and option markets ahead of corporate news events, whether these are anticipated in terms of their timing, as in the case of earnings announcements, or unanticipated, as for mergers and acquisitions (M&A). While previous work has successfully identified the *existence* of informed trading ahead of future news releases, the literature has not been informative about the particular strategies an informed investor would implement to maximize her benefits from private information. The optimal strategy depends, of course, on the private signal she receives, i.e., the quality of the tip and the type of future announcement.

Our objective is to understand how the nature of the private information affects the choice of strategy of informed investors for a range of potential announcements. There is significant heterogeneity in the information informed investors receive about (i) the timing of a corporate announcement, and (ii) its impact on stock prices, and this heterogeneity affects their choice of trading strategy. Thus, any study that focuses on only any one specific type of corporate event, albeit in detail, is limited in its predictive power for understanding how differences *across* event types affect informed trading. Our study is much broader in scope, since we study how informed investors choose the parameters of their option trading strategy ahead of corporate announcements, when they receive private but noisy signals about the characteristics of these events. From an academic perspective, it is interesting to better understand how informed investors trade differentially as a function of the characteristics of corporate announcements. From a practical perspective, such an exercise can serve as a guide to prosecutors and improve the detection of illegal insider trading. The analysis of such strategies can greatly narrow the scope of investigations of insider activity and, hence, improve the chances

[1]Frontline, "Preet Bharara: Insider Trading Is "Rampant" On Wall Street " January 7, 2014.
[2]http://www.sec.gov/spotlight/insidertrading/cases.shtml

of detection, in the face of limited prosecutorial resources.

We focus on informed trading in *options* for a variety of reasons, although we also look at the underlying market, where appropriate. First, a growing theoretical and empirical literature in finance and economics has pointed towards options markets as a profitable avenue for informed trading, and serves as a benchmark for any new analysis. Second, trading in options rather than stocks can be substantially more profitable for informed investors, given the leveraged exposures derivative securities allow traders to establish. Third, the options market offers traders a rich menu of instruments enabling them to optimize their trading strategies by choosing the option strategy, maturity, and moneyness. Given the large number of investable strategies, it is not clear, ex-ante, how an informed investor would choose to trade in the options market, and when she would implement her trade. In this study, we analyze what strategy an informed investor would choose to implement, conditional on trading in the options market.[3]

To frame our thoughts, let us consider the following two examples based on instances of illegal trading prosecuted by the Securities and Exchange Commission (SEC). In the first case, one day prior to the unexpected takeover announcement of H.J. Heinz by Berkshire Hathaway and 3G Capital on February 14, 2013, two rogue traders purchased 2,533 call options at a strike price of $65 and expiring in June 2013. At the time, the stock price was trading at $60.48, and the offer price on the announcement day was $72.50. Thus, while at the time of the purchase, the option was out-of-the money (OTM) with a ratio of the stock price to the strike price of 93%, it moved into the money following the announcement, and ended up generating illegal profits of approximately $1.8 million. In another instance, a rogue trader purchased 200 April call options at a strike of $20 on April 17, 2006, two days before a positive earnings announcement by Polycom, generating an ill-gotten profit of $22,000. Why did the Heinz traders purchase call options expiring in June at a strike of $65, and why did the Polycom trader purchase call options expiring in April at a strike of $20? How was their choice of trading strategy influenced by the type of future news, i.e., earnings vs. takeover

[3] John et al. (2003) examine how margin constraints influence an investor to trade in the options versus the stock market.

announcement, and by the quality of the tip? These are the questions we attempt to answer in this paper.

We first propose a theoretical framework for identifying option trading strategies, i.e., option type, strike price, and maturity, which maximize expected returns, net of transaction costs in illiquid markets for informed investors with private but noisy information. We assume that the private information consists of two signals, information about the *expected timing* of an announcement, and information about the *expected announcement return* on the underlying stock in reaction to news.[4] In addition to its expected value, we also consider the *precision* of each of the two signals, characterized by the uncertainty in the timing of the future announcement and the uncertainty of the future stock price reaction. For example, while earnings announcements are scheduled events, M&A announcements are typically unexpected, and their precise timing is unknown, even to many insiders. Similarly, while the announcement return on the stock of target companies of takeover announcements is, on average, greater than that on the stock of companies following surprises in earnings announcements, both events are marked by a heterogeneity in the distribution of stock returns, after the news become public.

One important feature of our theoretical framework is that it accounts for two important frictions prevalent in the options market. First, most options trade with *significant bid- ask spreads*. Their minimum bid-ask spread is defined in dollar terms implying substantially greater percentage bid ask spreads for options that are further away from the money given their lower prices. Second, most options do not trade below a *minimum price* of ten cents. Both these frictions can make trading OTM and deep-out-of-the money (DOTM) options prohibitively expensive (in terms of their implied volatility) and, therefore, severely limit the leverage investors can attain in the options market.[5] In addition, run-ups in implied volatilities ahead of scheduled news can substantially increase the cost of setting up a trading strategy. Using numerical analysis, we illustrate

[4]It is possible to extend our analysis to account for private but noisy signals about changes in the volatility of the underlying stock price distribution. This dimension is relevant in the presence of volatility trades on M&A acquiring companies, as suggested by Augustin et al. (2014). In this paper, we focus on a two dimensional signal for tractability.

[5]Multiple studies document that OTM options are overpriced relative to standard pricing models. Boyer and Vorkink (2014) report that intermediaries expect substantial premia when writing OTM options. Goyenko et al. (2014) show that the bid-ask spreads of OTM options are inflated by information asymmetry and demand pressures arising ahead of earnings announcements.

that these effects reduce the maximum expected returns to informed trading from unrealistically high levels of multiple millions of percent to levels similar to what is reported in SEC litigation cases of insider trading. Furthermore, these frictions heavily affect the set of parameters that maximize the returns to informed trading.

Amongst others, our framework generates the following predictions about the trading strategies of informed investors. First, market frictions including minimum prices and bid-ask spreads can heavily affect the trading behaviour of informed investors. Given market frictions, they trade options that are near the money and avoid OTM and DOTM options, as these become prohibitively expensive in terms of their implied volatility. The role of frictions is more limited for options with a higher Black and Scholes (1973) and Merton (1973) (BSM) value, including longer term options and options with higher implied volatility (whether permanently, or due to a temporary run-up in implied volatility ahead of a scheduled event). Synthetic call options enable investors to substantially reduce the effects of market frictions and increase the leverage on a private signal. However, establishing a synthetic call requires borrowing at (or close to) the risk free rate and is, therefore, restricted to sophisticated investors.

Second, changes in the uncertainty about the announcement return have a limited effect on the behavior of insiders. In contrast, the expected value of the announcement return is a primary determinant of expected returns to insider trading. In most instances, insiders will trade further OTM when anticipating announcement returns of a higher magnitude. However, this shift to OTM trading is limited by market frictions, as previously stated.

Third, the precision of the timing signal does affect the behaviour of informed investors. All else equal, higher event date uncertainty implies informed investors will trade in longer maturity options to avoid purchasing options that expire worthless. This implies higher costs of setting up any strategy with a positive theta. In fact, informed investors with a very precise timing signal can trade very briefly ahead of the event. Without a run-up in implied volatility – that is, if the event is not anticipated – they can achieve very high leverage by trading options with a short time to maturity. For scheduled events, implied volatilities and bid ask spreads will increase ahead of an event, due to uninformed speculation. This can substantially reduce attainable returns.

To validate our approach empirically, we first compare the normative model solutions from our framework to the characteristics of illegal trades implemented by rogue traders, as identified in a comprehensive sample of litigation records of civil and criminal prosecutions, which we hand collect from the web sites of the SEC and the U.S. Department of Justice (DoJ). We find that prosecuted trades closely resemble informed trading predicted by our theoretical framework. This diagnostic offers empirical support for our approach.

More specifically, consistent with the predictions, the uncertainty about the timing of M&A announcements is reflected in a higher time to maturity of options traded by SEC-detected insiders ahead of M&A announcements, compared to the maturities of option trades implemented ahead of earnings announcements. Furthermore, the moneyness of the traded options in the SEC sample decreases in the magnitude of the expected announcement returns. Ahead of M&A announcements, insiders establish bullish directional exposures by purchasing OTM call options with a median spot-to-strike price ratio of 93.9%. In contrast, both bearish and bullish trades implemented due to private information about negative and positive earnings announcements are made using ITM put and call options, respectively. The median spot-to-strike price ratio equals 96.3% for put and 104.2% for call options.

We further validate our approach by testing whether on days with illegal insider trading in a specific firm, insiders are more likely to trade in options that have higher expected returns according to our framework. We do so by estimating logistic regressions of a dummy variable indicating illegal insider trading in a specific option contract on expected returns. We compute the latter according to our framework as a function of the insider's private signal. For each day on which an option was traded by an insider, our sample includes all options written on the same stock that traded on this day. Indeed, expected returns are significant predictors of insider trading. Overall, these results indicate that our framework can provide guidance to regulators and researchers trying to identify illicit trading activity in the options market.

The sample of SEC litigations allow us to directly observe the trading activity of insiders and benchmark it against the predictions of our framework. However, the previously described results can be due to a selection bias if prosecutors naturally focus on trading activity matching the predictions of our framework. In the second part of our study, we, therefore, employ our framework in a broader context to compute expected returns to informed trading ahead of firm-specific news and document unusual trading in options with high expected returns.

More specifically, we identify suspicious activity in option markets prior to 30,975 "significant corporate news" (SCNs) identified between 2000 and 2014. We define SCNs as firm-specific news stories that can be linked to extreme price movements (EPMs). To construct our sample, we rely on the comprehensive RavenPack news database that reports news stories with millisecond timestamps. Our list of SCNs includes news from twelve different categories which feature a substantial amount of heterogeneity with respect to their announcement characteristics.

To the best of our knowledge, virtually all other studies on informed or insider trading in options focus on *one* individual type of event, such as M&A transactions, corporate divestitures, or earnings announcements.[6] Using a large and heterogeneous sample of SCNs instead has several advantages. First of all, it allows us to better understand how informed investors trade in relation to the type and quality of their private information. This cross-sectional heterogeneity in trading provides much richer information to regulators compared to a simple identification of unusual activity. Second, using a large sample of economically important events increases the power of tests for detecting informed trading activity. Finally, given that we can observe the exact timing of both the news and the price reaction, we eliminate uncertainty about the announcement time. Doing so eliminates any potential upward-bias in measures of suspicious trading activity due to event date

[6]A notable exception is the article by Cremers et al. (2015), who study how the difference between scheduled and unscheduled news affects an informed investor's trading behaviour.

uncertainty.[7]

Our empirical results are as follows. First, we document unusual trading activity ahead of news using two naive measures for the trading direction. The *pricing measure* used to test this hypothesis is the natural logarithm of the ratio of the implied volatility of OTM call options divided by that of OTM put options. The *volume measure* is the relative call volume, which we define as the dollar volume traded in all call options written on a stock on a given day divided by the sum of the call and put volume. Indeed, we observe significant differences in the time series of these measures ahead of positive versus negative news events.

In a second step, we verify whether the naive measures of directional option trading are in line with the our theoretical framework. We find that unusual trading activity picks up briefly ahead of scheduled events with no timing uncertainty, but increases several weeks ahead of events with timing uncertainty. These results are also in line with our theoretical framework, which suggests that informed investors maximize their expected returns when they trade shortly before an announcement when the uncertainty about the timing of the event is low. Vice versa, if the timing of the event is less certain, investors have higher expected returns if they start to trade earlier.

Finally, we address concerns that the previously described patterns are due to speculation in the options market. For instance, if investors are aware that a takeover will take place in the North American solar industry, they can use options to bet on price increases in all potential targets. Even though it is unlikely to observe such directional speculation for a large sample we additional analysis to address this concern. For this analysis, we directly employ our theoretical framework to construct new measures capturing suspicious trading activity. For each call (put) option-day, we compute hypothetical expected returns for a +10% (-10%) price jump. For each firm-day, we then compute the ratio of the volume of call (put) options with a high expected return to the total call (put) volume, which we label "volume ratio". Additionally, we calculate the "IV ratio" as the implied volatility of high expected return options divided by that of options with a low

[7] If information becomes public before the announcement date reported in a news database, increased trading activity prior to the reported announcement date can appear abnormal, although it simply reflects the reaction to the new information.

expected return. Using a multinomial logistic regression, we show that the put option volume ratio predicts negative corporate news, while the call option IV ratio predicts positive corporate news. Using this approach, we can predict positive and negative news in the short term (over the next three trading days) and even over the next ten trading days. These results cannot be explained by a potential sample selection bias and indicate that our theoretical framework enables us to identify informed trading activity in the options market.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and discusses our main contributions. Section 3 presents a novel framework for identifying option trades that maximize expected returns to informed traders with private but noisy signals, and compares the predicted solutions to prosecuted cases of illegal insider trading. Section 4 describes the construction of our sample of news events. Section 5 documents suspicious trading activity ahead of these events and demonstrates that our framework can be used to predict corporate announcements. We conclude in Section 6.

2. Literature Review and our Contribution

There is a growing body of research examining the nature and existence of insider trading, for which Bhattacharya (2014) provides a recent review. Early studies on (illegal) insider trading either have access to special proprietary data, or examine case studies of rogue trading. Using a sample of illegal insider trades prosecuted by the SEC from 1980 to 1989, Meulbroek (1992) finds that days of insider trading coincide with abnormal returns of 3%, and are responsible for the price-run ups prior to public news announcements. Cornell and Sirri (1992) use court records on illegal trades ahead of the 1982 takeover of Campbell Taggart by Anheuser-Busch to show that insider trading had a clear impact on stock prices and positively affected liquidity, while Fishe and Robe (2004) find that illegal trading negatively impacts market depth, based on the trades by brokers, who obtained advance access to information on 116 stocks released in a newspaper column.

More recent work has relied on publicly available litigation records on insider trading prosecutions to describe the characteristics of illegal options trades (Augustin et al., 2014), insider trading networks (Ahern, 2015), or the aggressiveness of prosecution (Guercio et al., 2015). Other work uses the holdings positions of institutional investors to point towards exploitation of private information by investment banks, ahead of mergers and acquisitions (Bodnaruk et al., 2009; Dai et al., 2011), or to contradict such abuses (Griffin et al., 2012). Cohen et al. (2010) suggest that private information flows between investors with former school ties. Moreover, some studies relate findings of volumes and returns that are correlated with future price jumps to illegal trading behavior in the stock market (Keown and Pinkerton, 1981; Agrawal and Nasser, 2012), in the credit derivative market (Acharya and Johnson, 2007), and in the options market ahead of the 9/11 terrorist attack (Poteshman, 2006) or M&A announcements (Augustin et al., 2014).

More generally, our work also relates to the large literature on informed trading in options markets ahead of major news announcements, such as analyst recommendations (Kadan et al., 2014), macroeconomic news (Bernile et al., 2015), the announcement of earnings (Goyenko et al., 2014), M&As (Cao et al., 2005; Chan et al., 2015; Kedia and Zhou, 2014; Augustin et al., 2014), spin-offs (Augustin et al., 2015), leveraged buy-outs (Acharya and Johnson, 2010), and the announcements of strategic trades by activist investors (Collin-Dufresne et al., 2015).

There are several important distinctions between the previous literature and our work in this paper. While there is a large theoretical literature that examines *whether* and *when* informed investors trade in the options markets, there is little attempt to understand *how* informed investors trade in the options market.[8] Thus, this literature implicitly assumes an underlying friction that gives the investor an incentive to migrate to the options market, but the question remains as to the strike price and maturity of the option chosen. First, we focus on the type of strategy, i.e., puts, calls, or a combination of both, as well as the moneyness, i.e., the strike price, and time to expiration, that the informed agent chooses. While previous work has successfully

[8]More specifically, prior research examines whether and when informed investors trade in the options markets in the presence of asymmetric information (Easley et al., 1998), differences in opinion (Cao and Ou-Yang, 2009), short-sale constraints (Johnson and So, 2012), or margin requirements and wealth constraints (John et al., 2003).

identified the *existence* of informed trading ahead of future news releases, the literature has not documented any details about the strategy an informed investor would implement to maximize her benefits from private information.

Second, we examine multiple events jointly, rather than focusing on a specific type of event individually. This is useful for several reasons. Heterogeneity in event characteristics influences the optimal trading decision. Thus, any study that does not take account these cross-sectional differences would be unable to explain how informed investors trade differentially as a function of the characteristics of corporate announcements. This is highly relevant, though, especially for litigators engaged in a forensic analytics of rogue trading. Third, increasing the number of events further improves the power of the statistical tests, which we can, therefore, conduct at a more granular level.

3. Trading Strategies of Informed Investors

For an equal dollar investment, an informed investor obtains more "bang for the buck" in the options market compared to the stock market. This is because derivatives allow for more leveraged exposures than the underlying cash market. To give an illustrative example, a few days ahead of a negative earnings surprise announced by Walgreen's on October 1, 2007, Thomas Flanagan, a former vice president at Deloitte and Touche LLP with material private information on multiple client firms, and his son, bought 485 put options on the stock at strike prices of $45 and $47.5, expiring in October 2007, for a total cost of $46,619. When the firm announced its first earnings decrease (relative to the prior quarter) in almost a decade, its shares fell by 15% and the insiders sold their options, realizing a profit of $268,107, or 575% of their investment. In 2010, the SEC charged the Flanagans with insider trading on multiple occasions that resulted in total illicit profits of $487,000. The suspects settled for a disgorgement of ill-gotten profits and a civil penalty of more than $1.1 million.

The previous example begs the question of why the insiders chose the $45 and $47.5 strike options with a short time to expiration. As we formally show in this section, the benefits from illegal insider trading vary substantially across the wide spectrum of insider trading strategies, in terms of both strike price and maturity. Our objective is to improve the identification of illegal insider trading by better understanding the trading strategies that maximize expected returns to investors with noisy private signals about the timing and stock price reaction of future news announcements. To achieve this objective, we first propose a general framework for calculating the expected returns to informed trading as a function of the type, quality, and strength of the private signal received by the informed trader. We then compare our predictions with actual insider trading cases documented in a sample of civil enforcement actions initiated by the SEC.

3.1. A Theory of Informed Trading

The objective of our study is to understand how informed investors choose to trade in option markets given the strength and quality of their private signal. To do so, we assume that the informed agent is risk neutral; hence, the choice of option contract(s) traded by her depends only on its expected return net of transaction costs, given that she is capital constrained. We calculate the expected return to buying an option today (at t_0) and to selling it after a news-induced jump (at $t_1 = t_0 + \Delta t$) as

$$\mathbb{E}[R] = \frac{\mathbb{E}[P_{bid,\ t_1}]}{P_{ask,\ t_0}} - 1 \tag{1}$$

where $[P_{bid,\ t_1}]$ denotes the bid price at which the investor expects to sell the option and $[P_{ask,\ t_0}]$ is today's option ask price as observed in the market. Analogously, we compute expected returns of trading strategies involving multiple securities by summing up the expected bid and observed ask prices of all securities in the numerator and denominator, respectively. We do not account for margin requirements as they are zero for long options positions, which we consider in this study. In the BSM framework without dividend payments, the expected return to option trading around a news event is given by

$$\mathbb{E}[R] = \frac{\mathbb{E}\left[\theta(S_0 e^{\kappa}, T_0 - \Delta t, K, \sigma, r)\right]}{\theta(S_0, T_0, K, \sigma_0, r)} - 1 = \frac{\mathbb{E}\left[\theta_1\right]}{\theta_0} - 1, \tag{2}$$

where $\theta(\cdot)$ denotes the BSM value of a European call or put option as a function of the underlying stock price S_0, the option's strike price K, the option's time to maturity T_0, and the risk-free rate r. Following Cremers et al. (2015), we incorporate the run-up in implied volatility ahead of scheduled events based on Dubinsky and Johannes (2006) by defining $\sigma_0 = \sqrt{\sigma^2 + \frac{\sigma_j^2}{T_0}}$. For unscheduled events, $\sigma_0 = \sigma$. σ is the usual implied volatility excluding run-up and σ_j the volatility of the jump anticipated by (uninformed) investors ahead of a scheduled event.[9] Throughout this paper, we follow Cremers et al. (2015) and – for scheduled events – assume a jump size volatility of $\sigma_j = 0.1$.

We next account for market frictions by introducing bid-ask spreads α and a minimum option price P_{min} to be consistent with a realistic trading setting. We can rewrite the previous expression as

$$\mathbb{E}[R] = \frac{\mathbb{E}\left[\max\left(\theta_1 - 0.5\alpha_1, P_{min}\right)\right]}{\max\left(\theta_0 + 0.5\alpha_0, P_{min}\right)} - 1. \tag{3}$$

Finally, we take into account the perspective of an informed investor who receives two private signals about future news. The first is information about the *timing* of the news event. As we assume that she unwinds her position instantly after the news-induced jump, the notation for the timing of the jump corresponds to that for the time between the opening and the closing of the option position, Δt. The second signal relates to information about the *magnitude* of the jump induced by the news, κ. Both of these signals may be noisy. Denoting their joint probability density function by $\phi(\kappa, \Delta t)$, the expected return to the option strategy is the

[9]Informed trading due to changes in σ are easy to incorporate using a simple extension of our framework. This would distract us, however, from the focus of our study, while having only a marginal impact on predicted trading behavior, if any. Results not reported in this article reveal that while trading on changes in the implied volatility does not offer high expected returns to insiders, it can still be rational to trade in vega strategies, e.g., straddles, if their signal is very noisy. These results are available upon request.

probability-weighted average

$$\mathbb{E}[R] = \frac{\int_{\kappa} \int_{\Delta t} \phi(\kappa, \Delta t) \max\left(\theta_1(\kappa, \Delta t) - 0.5\alpha_1, P_{min}\right) d\kappa\, d\Delta t}{\max\left(\theta_0 + 0.5\alpha_0, P_{min}\right)} - 1. \tag{4}$$

We account for illiquidity in the option market by using the following rule: Whenever the BSM option value adjusted for half the bid-ask spread is below the minimum price, as can be expected for DOTM options, the market price equals the minimum price. Beyond market liquidity, bid-ask spreads and minimum prices are driven by the minimum tick size dictated by the Chicago Board Options Exchange (CBOE). Since the year 2000, the minimum tick size for most options equals five cents if traded below three dollars, and ten cents otherwise. Exceptions were introduced in the CBOE's experimental Penny Pilot Program, the first phase of which commenced on January 26, 2007. As part of that program, the minimum tick of heavily traded options was decreased to one and five cents for options priced below or above three dollars, respectively.

We have established a simple expression for expected returns to informed trading under market frictions. Under the simplifying assumption that informed investors attempt to maximize their expected returns, we can use this expression to identify the strike price, maturity, and type of the option contract(s) they choose to trade in. Before examining the expected returns for alternative option strategies and varying private signals, we illustrate the implications of market frictions and noise in the private signal.[10]

The two *market frictions* that we account for are minimum option prices and bid-ask spreads, both of which reflect the limited liquidity in the options market. Figure 1 shows the effect of market frictions on expected returns. Each graph plots the expected returns to informed trading in call options computed using Equation 4. For the purpose of illustration, we consider a signal that suggests a future price jump of κ=20% in Δ_t=3 days, without any uncertainty about the magnitude of the jump or about the timing of the news announcement, i.e., σ_κ=0, $\sigma_{\Delta t}$=0. Furthermore, S_0=10, r=0.03, and σ=0.4. The upper two graphs in Figure 1 are based on the assumption that there are no market frictions. The bid-ask spread and the minimum

[10] The insider's problem presented in this paper cannot be solved analytically. All of our results are based on numerical solutions.

price are equal to zero. Under these assumptions, the BSM value of an OTM option close to expiration is a small fraction of a cent. Buying an OTM option at such a low price, and selling it once it is ITM after the news-induced jump, yields a return of more than 1.8 million percent! The introduction of minimum prices highlights that it impossible to generate such unrealistically high returns in a more realistic market setting that takes into account such frictions. The lines in the two lower graphs that are labelled "market frictions" assume a bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining equal. The lines labelled "scheduled" assume a Dubinsky and Johannes (2006) run-up in implied volatility ahead of the event. Even without this run-up, market frictions reduce maximum expected returns to less than 2,000%, clearly, a more realistic value.[11]

The illustrative example underscores the importance of accounting for non-zero minimum prices, bid-ask spreads, and potential run-ups in implied volatility, as these restrict the leverage an informed investor can realistically obtain in option markets. Thus, our simple framework generates a trade-off faced by the informed investor so that DOTM options are not those enabling return maximization. We now turn to discuss the realistic magnitudes of these two market frictions. Panel A of Figure 2 plots the evolution of the average (dotted line) and median (dashed line) bid-ask spreads of equity options reported in the OptionMetrics database. Averages and medians are computed over all contract-days with a trading volume of at least 100 contracts and non-negative bid-ask spreads. Circles mark call options, crosses mark put options. Median (average) spreads reduced substantially over time, from 25% (23-24%) in 1996 to 5% (10-11%) in 2010, with a spike in 2008.

An option's minimum offer price is given by its minimum tick size. While this implies that DOTM options may be traded at five cents – or since 2007 even at one cent if they part of the Penny Pilot Program – the minimum offer prices reported in the OptionMetrics database are higher for the vast majority of options. Panel B displays the evolution of the minimum (dotted line) and the first percentile (dashed line) of option

[11] For instance, in our sample of actual insider trading cases documented by the SEC, insider trading around M&A announcements produces average returns of 1,297%, as shown in Table 1.

prices below three dollars. Minima and percentiles are computed over all contract-days with a trading volume of at least 100 options. Until 2007, the time series of observed minima reflects the described minimum CBOE tick size. The increase in the minimum price in the years 2008 to 2010 can be ascribed to the exceptional period of the financial crisis. Most of the time, however, as illustrated by the first percentile of option prices below three dollars, empirically observed minimum prices are equal to or above 10 cents. Thus, the regulatory minimum prices do not seem to be a binding constraint. The fact that DOTM options are rarely offered at the possible minimum price of 5 cents even if their "fair" (i.e. BSM) value is lower than that, may be explained by risk aversion, informed trading, adverse selection, or other factors such as inventory costs and illiquidity. Writing DOTM options offers little return, but a potentially tremendous downside to traders. Even for risk-neutral market makers, the cost of trading with an informed counterparty may prevent investors from offering DOTM options at the minimum regulatory prices. Indeed, as shown by Goyenko et al. (2014) using intraday transactions data, the bid-ask spreads of OTM options are driven by information asymmetry and demand pressures increasing ahead of earnings announcements. Boyer and Vorkink (2014) report that intermediaries expect substantial premia when writing OTM options and suggest that they "compensate intermediaries for bearing unhedgeable risk when accommodating investor demand for lottery-like options."[12]

Minimum prices render the trading of DOTM options expensive, which is also reflected in the high implied volatilities of most DOTM options and, perhaps, the low trading volume in even OTM options. While it might be intuitive that informed traders, who expect a significant jump in stock prices, are best off purchasing DOTM or at least OTM options, we formally show that these do not always offer the highest *expected* return to informed investors. This is in particular true if the investor faces uncertainty about the magnitude of the future price jump and uncertainty about the timing of the jump. In other words, the choice

[12]This argument relates to prior work on the inelasticity of the option supply curve, along the lines analyzed theoretically by Garleanu et al. (2009) and empirically by Bollen and Whaley (2004) and Deuskar et al. (2011). For an earlier overview of research on empirical option pricing, see Bates (2003).

of option strategy depends on the noise associated with the private signal. We rationalize why in most cases it is optimal to trade in options that are only slightly OTM. These findings appear realistic as such patterns are consistent with observed illegal insider trades, such as the previously highlighted trade by the Flanagans, who purchased put options with a strike price of USD 47.5, when the underlying was trading between 47 and 48 USD.

Though important, the effect of uncertainty or *noise* in private information, i.e., uncertainty about κ and Δt, on expected returns is less significant than that of market frictions. The graphs in Figure 3 plot expected returns to informed trading in call options computed using Equation 4. We use the previous example to illustrate the impact of uncertainty about the jump size and timing of the announcement. Thus, we use an expected news-induced jump of κ=20% in Δ_t=30 days. Bid-ask spreads equal \$0.05 and the minimum price is \$0.10. Furthermore, S_0=10, r=0.03, and σ=0.4. The left (right) graph plots expected returns as a function of the time to maturity (strike price) of the option. On each side, the strike price (maturity) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima of each function in the left and the right graph are identical. In each graph, the four lines represent different magnitudes of uncertainty. Bid-ask spreads equal \$0.05 and minimum price \$0.10. For the given set of parameters, maximum expected returns decrease significantly in the uncertainty of the timing of the announcement, $\sigma_{\Delta t}$. The impact of uncertainty about the jump magnitude, σ_κ, on expected returns is positive, but it is less pronounced. Thus, higher uncertainty about the timing of public news announcement reduces expected returns and incentivizes the investor to choose longer maturity options and deeper OTM options compared to the benchmark case, without any timing uncertainty. On the other hand, higher uncertainty about the magnitude of the announcement *increases* the expected returns and results in a choice of shorter-term options that are further OTM.

3.2. *Expected Returns of Different Trading Strategies and Private Signals*

Having illustrated the effects of market frictions and noise in the private signal on expected returns, we now explore how the *type* and the *quality* of an informed investor's private signal affect the strike price, maturity, and type of option contract she needs to trade to maximize her expected return. This helps pinpointing the trading activity on which a forensic analyst should focus.

The upper two graphs in Figure 4 (Figure 5) plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the time to announcement, Δt (the expected jump in stock prices, κ).[13] The lower graph displays the maximum expected return $E[R]^{max}$. In each figure, results are shown for three different parameter sets describing the private signal.

Figures 4 and 5 illustrate several important takeaways generated by our framework.[14] We refer to the upper, middle, and lower graphs in Figures 4 and 5 as Figures 4a, 4b, 4c, and 5a, 5b, 5c.

The first set of implications is related to the strike price maximizing expected returns (K^{max}). κ is a key determinant of expected returns (Figure 5c). Naturally, the lower κ, the higher the moneyness of the traded call option (Figure 5a).However, for many parameter combinations, informed investors do not trade OTM. For instance, for the parameter sets plotted in Figure 5a, insiders will trade ATM or even ITM for anticipated jumps of up to 10%. Furthermore, the kink in the function implies that once κ reached a certain level, insiders will only marginally reduce the moneyness given an additional increase in κ. Options that trade DOTM thus do not maximize returns to informed trading. The kink is due to the market frictions incorporated in our framework. Their impact on insider trading is most pronounced for options with a low theoretical value, for instance options with low implied volatility and short time to maturity. Amongst others, this explains why K^{max} shown in Figure 4a is lower for options with a short than for those with a medium time to maturity.

[13]Expected returns are computed according to Equation 4.

[14]Of course, the plots are restricted to a limited number of parameter combinations. However, the main takeaways discussed in this section are robust to changes in parameters. We can provide additional results upon request.

The second set of implications is related to the time to maturity of the option maximizing expected returns (T^{max}). The longer the period between the time an insider trades and the time of the anticipated announcement Δt, or the higher the uncertainty about the announcement date, the longer the maturity of the options an insider needs to trade to avoid that they expire worthless (Figure 4b). All else equal, the need to trade in longer term options decreases expected returns to insider trading (Figure 4c).

We include additional graphs for the case of scheduled events, and for different trading strategies in the Appendix to this paper. Figures A1 and A2 illustrate that expected returns to informed trading in call options are lower for scheduled events. Figures A5 and A6 show that synthetic calls enable investors to reduce the impact of market frictions and substantially increase expected returns, as OTM or even DOTM options can be created by trading the underlying together with ITM or DITM options, which are substantially less affected by market frictions.[15] However, trading synthetic call options requires an investor to partly finance his positions by borrowing at the risk free rate and is thus likely restricted to sophisticated investors.[16] Accordingly, based on a full examination of all civil and criminal litigations for illegal insider trading, we note that almost no litigation refers to insider trading implemented through the use of synthetic options positions. Finally, Figures A3 and A4 demonstrate that the patterns observed for informed trading in call options are very similar for put option trading, implying that the above insights extend to the latter.[17]

To summarize, expected returns from options strategies can differ tremendously as a function of the level and precision of private signals. Regulators and researchers trying to pinpoint suspicious trading can account for these differences using a framework as proposed in this study. Such guiding principles may allow them to focus on trading in those contracts that are supposedly most attractive to informed investors. Appendix A

[15]Even though DITM options can, in absolute terms, have higher absolute bid-ask spreads then DOTM options, the percentage spread of DITM options relative to their price tends to be substantially lower, given that prices include a high intrinsic value. For the same reason, minimum prices are irrelevant to the pricing of ITM options.

[16]We ignore synthetic put options, which can be created by combining a long call position with a short position in the underlying, as these imply significant margin requirements. While these can be incorporated in our framework, this is beyond the scope of our analysis. In brief, any significant margin requirement will substantially reduce an investor's leverage and thus, heavily reduce returns to insider trading.

[17]Our framework also allows the analysis of informed trading in volatility strategies such as straddles. We do not include results for the sake of brevity but can provide them upon request.

provides a structured summary of the implications of our theoretical framework.

3.3. Empirical Predictions and Development of Hypotheses

Our objective is to improve the detection of illicit trading activity. To achieve that goal, our framework needs to be applicable. The numerical analysis, based on our conceptual framework, suggests several testable predictions that we verify using two different datasets. First, a hand-collected dataset of SEC litigations complemented with trading data enables us to observe the characteristics of illegal insider trading ahead of M&A announcements, as well as positive and negative earnings announcements. We use this data to verify the following hypotheses.

H1: *Ahead of M&A announcements, insiders trade*

(a) earlier (relative to the announcement date),

(b) in options with greater time to maturity, and

(c) in options that are further out of the money,

than ahead of earnings announcements.

We test this hypothesis by comparing the trading activity of illegal insiders for the three different sub-samples of SEC litigations.

H2: *On option days with illegal insider trading, insiders are more likely to trade in options that have higher expected returns.*

We test this hypothesis by estimating logit regressions of a dummy variable indicating illegal insider trading in a specific option contract on expected returns. We compute the latter according to our framework as a function of the insider's private signal. For each day on which an option was traded by an insider, our sample includes all options written on the same stock that traded on this day.

Second, we study patterns in the pricing and volume of options ahead of significant corporate news. In a first step, we employ simple measures of directional option trading that do not require the calculation of expected returns to test the following hypothesis.

H4: *There is unusual option trading activity ahead of significant corporate news.*

The pricing measure used to test this hypothesis is the natural logarithm of the ratio of the implied volatility of OTM call options divided by that of OTM put options. The volume-based measure is the relative call volume, which we define as the dollar volume traded in all call options written on a stock on a given day divided by the sum of the call and put volume. These measures are more naive and simple to compute than those used in recent studies including Pan and Poteshman (2006), Roll et al. (2010), Johnson and So (2012), and Ge et al. (2015). If we find evidence for unusual trading activity based even on our naive measures, more evolved measures will arguably provide even stronger results.

The next hypotheses are again based on the naive measures of directional option trading, and reflect the predictions about the behaviour of informed investors generated using our theoretical framework.

H5: *Ahead of positive (negative) announcements with a higher event date uncertainty, relative call option volume will start to increase (decrease) earlier than for events with low event date uncertainty.*

H6: *Ahead of positive (negative) announcements with a higher event date uncertainty, the ratio of call to put implied volatility will start to increase (decrease) earlier than for events with low event date uncertainty.*

We test these hypotheses by comparing the time series of each measure for scheduled and unscheduled events. Finally, we employ our theoretical framework to construct new measures capturing suspicious trading activity. For each call (put) option-day, we compute hypothetical expected returns for a +10% (-10%) price jump. For each firm-day, we then compute the ratio of the volume of call (put) options with a high expected return to the total call (put) volume. Additionally, we calculate the ratio of the implied volatility of high expected return options to low expected return options. For brevity, we label these measures “volume ratio” and “IV ratio” and use them to test the following hypothesis.

H7: *The call (put) volume ratio predicts positive (negative) corporate news.*

H8: *The call (put) IV ratio predicts positive (negative) corporate news.*

We test these hypotheses by estimating multinomial logit regressions of a variable indicating whether (i) no, (ii) a positive, or (iii) a negative corporate event will occur over the next days on the call and put volume and IV ratios.

3.4. Characteristics of Illegal Insider Trading

In this section, we compare the predictions from our theoretical framework to illicit insider trades registered in civil and criminal litigations initiated by the SEC and the DoJ. To do so, we build a dataset comprising actual insider trading activity in equity options from civil litigation records obtained from the SEC, and criminal litigation records obtained from the DoJ.[18] We focus on the subset of SEC litigation cases related to insider trading in options prior to M&A and earnings. These constitute a particularly interesting benchmark for our predictions. M&A announcements are not scheduled and thus exhibit timing uncertainty. However, an insider may have information about the premium, allowing a relatively precise prediction of the change in stock price following the announcement. Kappa uncertainty is thus low. Earnings announcements are different. While they are scheduled ($\sigma_{\Delta t} = 0$), it can be more difficult for an insider to estimate the price impact of earnings news. We assume Kappa uncertainty to be substantially higher for earnings than for M&As.

We source information on litigations related to M&A and earnings announcements from the website of the Securities and Exchange Commission.[19] Similar to Augustin et al. (2015), we first scan all litigation files for cases involving insider trading with options by searching for the keywords “insider” and “options,” as well as “earning” or “earnings”. In a next step, we manually extract variables from the files. These include the name of the firm subject to insider trading, the dates at which options were traded, the number of options traded, the strike price and maturity of the option, the option type, and the date at which the firm was expected to release the pricing relevant news. We restrict the sample to cases for which one or more insider trading dates and the information release date fall into our sample period from 1996 (when OptionMetrics data starts) to 2010 (when our Capital IQ data used in the second part of this study ends),

[18] Detailed documentation on these cases is published under www.sec.gov/litigation.
[19] All civil litigation records are publicly available on the website of the SEC, www.sec.gov/litigation.

and to options written on US-American common stock. In a last step, we match observations with sufficient detail to specific option contracts covered by the OptionMetrics database, using information from the Option Price files. Table 1 reports summary statistics for our final sample of SEC litigation cases.

The characteristics of actual illegal insider trades offer empirical support for the previously introduced framework. Amongst others, the timing uncertainty of M&A announcements is reflected by a higher time to maturity of options traded by insiders ahead of M&A relative to earnings announcements. Furthermore, the moneyness of the traded options decreases in the magnitude of expected returns. Ahead of M&A announcements, insiders bet on substantial positive returns by purchasing OTM call options with an average spot to strike price ratio of 90.67. In contrast, insiders trade on price changes due to positive (negative) earnings announcements using call (put) options that are, on average, ITM and have an average spot to strike ratio equal to 104.7 (90.7). We further observe significant market frictions. Even the 5th percentile of option prices is twenty cents or higher, and median bid-ask spreads vary between 15 and 18 cents. Finally, option returns are by far the highest for insider trades ahead of M&A, and so is the percentage of insider trading activity. Implied volatilities are higher for options traded by insiders ahead of earnings announcements, which is consistent with increasing volatility in the underlying asset and increased premia for information asymmetry ahead of scheduled events.[20]

In addition to comparing the characteristics of the illegal insider trades to the predictions of our framework, we use the SEC litigation data to verify more directly if our approach enables the detection of insider trading in options. Table 2 reports results from logit regression of an indicator whether – according to the SEC Litigation files – an insider traded in a specific option contract or not. For each day on which an option written on a stock was traded by an insider we include all options written on the same stock that traded on this day. The dependent variable flags the option traded by the insider and equals one for all 358 observations in our SEC litigation sample. Explanatory variables include the percentile rank of expected returns ($\mathbb{E}[R]$

[20] See Goyenko et al. (2014).

Rank) and the Acharya and Johnson (2010) "bang for the buck" measure.

Results show that the probability of insider trading indeed increases in the expected return to informed trading computed according to our framework. The result is robust to controlling for the "bang for the buck" measure. This suggests that our approach can provide regulators and researchers with guidance on how to improve the detection of insider trading.

However, it is possible that the results presented in this section are (partly) due to a sample selection bias. If prosecutors intuitively focus on trading activity matching the predictions of our framework and simply do not uncover other insider trading, this could induce the results reported previously. In the subsequent analysis, we therefore benchmark predictions from our framework against suspicious trading activity observed ahead of a large sample of corporate news, and to predict such news in the aggregate cross-section of stocks.

4. Identifying Significant Corporate News

Our objective is to exploit the conceptual framework of informed trading to improve the identification of unusual trading activity. In the subsequent empirical analysis, we employ it to explain trading patterns prior to significant corporate news (SCNs) and to predict such news. As detailed subsequently, these are news events that we can link to extreme price movements (EPMs) of stocks. This section outlines how we construct our sample of SCNs.

When studying informed trading ahead of events, using a sample of SCNs instead of a broad sample of a specific event such as an M&A or earnings announcement has multiple advantages. First, we can study different types of corporate events, rather than focus on one individual type of event.[21] This enables us to exploit the heterogeneity in announcement characteristics to understand how informed investors trade in options. In this study, we explore trading patterns ahead of different types of SCNs including analyst recommendations, earnings announcements, corporate guidance, M&As, product development, management

[21] For example, Acharya and Johnson (2010) examine only leveraged buyouts, Augustin et al. (2014) only M&As, and Augustin et al. (2015) only 426 spin-offs.

changes, changes in dividends or financing, and others. Second, using SCNs as a starting point yields a sample that is larger and comprises economically more meaningful insider trading opportunities. This increases the statistical power of the statistical analysis. Third, given that the timestamp of an EPM and thus the SCN can be observed precisely using market data, we are sure to identify the moment news gets incorporated into prices. We thus eliminate event date uncertainty which can upward bias measures of unusual trading activity. In the following, we first describe how we identify EPMs, and then outline how we associate them with news events to finally obtain a sample of SCNs.

4.1. Identification of EPMs

Our sample period begins in 2000, the first year for which information from RavenPack, our primary news data set, is first available, and ends in 2014. To obtain a list of EPMs, we collect information on stock returns and prices, security type, the number of shares outstanding, and trading volume from the Center for Research in Security Prices (CRSP). We retain all common stocks (sharecode 10 and 11) that trade on the AMEX, Nasdaq or NYSE, for which all variables are available, resulting in a total of 17.5 million daily return observations. We exclude stock days with a lagged market value (the market value as of the previous trading day) below ten million USD or a lagged stock price below five dollars as such securities are often illiquid and exhibit higher levels of market microstructure noise. Furthermore, we delete all stocks for which not a single news headline is reported in the RavenPack news database during our sample period.

We obtain a list of 138,121 EPMs from the remaining 11.4 million daily observations. We classify a stock day observation as an EPM if it is a jump as defined by the Lee and Mykland (2008) method for jump detection or if the return on that day is above or below all returns observed during the preceding 252 trading days. We additionally require the availability of stock market data for at least 189 of the past 252 trading days.[22] In sum, our definition of EPMs is most closely related to the one used by Brogaard et al. (2015).

[22]For details on the Lee and Mykland (2008) approach for jump detection, see Appendix B. Amongst others, the method is used by Bradley et al. (2014) to examine the impact of analyst recommendations on stock prices.

They define EPMs at ten-second intervals as jumps identified by the approach proposed in Lee and Mykland (2012), which is more suitable for such high frequencies than the Lee and Mykland (2008) method used in this paper. In robustness checks, they alternatively label ten-second returns with a magnitude in the 99.99th percentile. In a final step, we match this list to the OptionMetrics and Compustat databases. As we are interested in informed trading in option markets, we exclude all EPMs of stocks on which there is no option written that traded once or more during the 63 trading days prior to the EPM. We further delete observations which we cannot match to Compustat. Our final sample includes 83,653 EPMs – 50.9 percent of which are negative – observed for 4,131 securities on 3,761 different dates between 2000 and 2014.

4.2. Associating EPMs with News

Early doubts cast on the relevance of news for asset pricing have recently been rectified.[23] Boudoukh et al. (2013) use textual analysis to demonstrate that an improved identification of relevant news stories results in a tighter link between stock prices and news. Bradley et al. (2014) document that after correcting the time stamps of analyst recommendations, these become an important determinant of Lee and Mykland (2008) jumps. More anecdotally, Lee and Mykland (2008) report that only "one or two" of 24 detected jumps were not associated to news.

We therefore expect a significant part of EPMs to be driven by news that investors incorporate into prices. Understanding what news story (most likely) induced an EPM is important for our study, as the type of news can affect both the probability of informed trading, as well as informed trading strategies. Acharya and Johnson (2010) argue that the probability of insider trading increases in the number of insiders in private-equity buyouts; results reported by Augustin et al. (2014) indicate that insiders in M&A deals employ multiple investment strategies involving options written on the target and acquiring firm's stock. In Section 3, we showed that the return-maximizing options trading strategy depends on the timing uncertainty and the magnitude of the stock price reaction of the future announcement. Both these parameters vary across

[23]See Roll (1988)'s presidential address to the AFA.

different types of events. For example, the timing uncertainty is zero for scheduled events, such as earnings announcements, but it can be high for unscheduled events. The direction and magnitude of an announcement return may be easier to predict for an M&A deal than for a change in management.

Our primary source for news data is the RavenPack News Analytics DowJones Edition. RavenPack employs textual analysis to identify companies, news categories, and news relevance in Dow Jones news articles and Press Releases published since the year 2000. Each news story has a milisecond precise time stamp. Over our sample period, the data includes 7.98 million corporate news stories for which a US based firm and a category were identified. We discard all news stories for which the relevance or novelty score is below its maximum of 100, as well as all stories of firms which we are not able to identify in the CRSP and Compustat database. Finally, we delete all news about the stock, including articles on stock gains and losses, order imbalance, and technical analysis, as these may have been caused by an EPM rather than being the reason for the EPM. These criteria result in 3.3 million news stories.

Especially large firms appear in the news frequently and not all news stories that co-occur with EPMs caused them. To associate specific news stories with EPMs, we proceed as follows. Similar to Bradley et al. (2014), we estimate logistic regressions to separately identify the determinants of positive and negative EPMs. More specifically, we regress an indicator of positive or negative EPMs on variables indicating RavenPack news categories. The coefficients obtained from these regressions are the log of the odds-ratio, which has a straightforward interpretation. For coefficient *i* it indicates by what factor the odds of observing an EPM changes if news are reported (only) in category *i*. For instance, on a day with no other reported news, the odds of observing an EPM increase by a factor of 3.14 if news are published that earnings per shares are above expectations.

The sample includes all 11.4 million stock-days included in the sample for which we estimate EPMs.[24] For a given stock-day, a news indicator is set equal to one if news in that category were reported for the

[24]Details on the sample selection are included in the previous section.

stock between 4pm on the previous trading date and 4pm of the given day. Of 527 RavenPack categories for corporate news, we ignore all categories for which not a single news observation is made on a positive (negative) EPM day and include indicator variables for all 80 (81) remaining categories.

Tables A1 and A2 only report statistics for all indicator variables that are significant at the one percent level. To account for multiple hypothesis testing we use Bonferroni adjusted p-values, implying a minimum t-value of 4.12. A detailed discussion of these results is beyond the scope of this paper. Overall, results are intuitively appealing. Events associated with returns of high magnitude such as M&A announcements or negative news about clinical trials have high odds ratios. In line with Bradley et al. (2014), analyst related news are important determinants of EPMs. We use these results to associate news and EPMs. First, we assume that only news that are significant determinants of EPMs (i.e. all news in the categories reported in Tables A1 and A2) can explain EPMs. Second, in case two or more news headlines for a firm are published between the end of the previous trading date and the day of the EPM, we associate the one with the highest odds ratio with the EPM. *We define an SCN as an EPM that we can explain by a news headline using this approach.*

We complement the RavenPack database with information on earnings news from Compustat's Capital IQ Key Development (CIQKD) database and quarterly earnings announcement dates from the Compustat Quarterly files. We use this information to distinguish between scheduled SCNs – which define as SCNs on the day or the day after an earnings announcement – and unscheduled SCNs that do not occur with earnings. This matters in our analysis, as there is a run up in implied volatilities ahead of scheduled SCNs. Similar to Cremers et al. (2015), we assume only news published on earnings announcement days to be scheduled.[25]

Table 3 reports descriptive statistics for the sample of positive and negative SCNs for each news category. Not surprisingly, news about a firm being acquired are associated to the highest returns and almost always

[25] The authors assume only earnings news to be scheduled. However, many other news, for instance related to financing, product releases etc are published on earnings announcement dates. Investors trading in options ahead of these will also face the pre-earnings run-up in implied volatilities, which affects expected returns. We therefore consider all news released on earnings announcement dates as scheduled.

induce heavy trading. Negative news about drug development are comparable even though the subsample is substantially smaller. EPMs which we cannot associate to news using the above approach (and which we thus do not classify as SCNs) often do not occur on days with very high trading volume, indicating that they may partly be due to the impact of trading on the prices of illiquid stocks rather than fundamental news. We ignore this category of EPMs in the subsequent analysis as such events may be noise that does not enable insider trading.

The heterogeneous nature of our event sample allows us to understand how informed investors can leverage different types of private signals. Table 4 describes expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category included in our sample. Expected returns are computed using Equation 4, assuming that informed investors trade ten days ahead of unscheduled news and one day ahead of scheduled news. The anticipated stock price reaction and its uncertainty are equal to the average and standard deviation of the return in each category, as reported in Table 3.

The median and 90th percentile of expected returns are substantially higher for events with strong stock price reactions. In most categories, trading ahead of scheduled news enables a higher leverage. This is in line with the high expected returns of short term options traded briefly ahead of an event documented in Section 3. However, expected returns computed for an actual dataset rather than numerical analysis reveal that the benefit of trading shortly ahead of an event are limited. For instance, the median expected returns to informed trading ahead of positive scheduled and unscheduled analyst opinions equal 120.2 and 103.8 percent, respectively. The difference between the subsamples of scheduled and unscheduled events is larger for the 90th percentile. This is simply due to the fact that in many cases, no or only a few options expiring directly after an event exist. While in theory, a precise timing signal enables substantial leverage, the effect reduced by the limited number of option contracts informed investors can trade in.

5. Identifying Informed Trading Prior to SCNs

In the previous section, we outlined how we construct our sample of SCNs. Put simply, these are strong price movements co-occurring with news announcements in subject categories known to induce strong price movements. The requirement of large price movements implies that profits to informed trading ahead of SCNs are economically large. Requiring the co-occurrence of important news increases the chances that a significant number of insiders to an event exist. We therefore argue that informed trading ahead of an SCN is more likely than (i) ahead of a news event that is not accompanied by a significant price reaction and (ii) ahead of a strong price reaction that cannot be explained with a news announcement. In sum, we consider our sample as particularly suited to study patterns in informed trading.

Before benchmarking such patterns against the predictions of our framework, we provide evidence supporting our assumption that SCNs are preceded by informed trading. Figure 6 plots measures of directional trading activity ahead of positive and negative events together with the difference between the two subsamples. The two measures of directional trading activity are the ratio of call volume to total option volume and the implied volatility of OTM call options to that of OTM put options. As previously acknowledged, these measures are more naive than measures used in recent studies[26] Amongst others, they do not capture whether option positions are closed or opened and are partly based on datasets not used in this study. Evidence for unusual trading activity based on our simple measures can be expected to be be more pronounced for more informative measures.

In line with our assumption, we observe suspicious directional patterns ahead of SCNs. The ratio of call to total option volume drops substantially ahead of negative news, meaning that the relative amount of traded put options, enabling bets on negative price movements, increases. This pattern cannot be observed ahead of positive events, ahead of which there is no significant change in the volume based measure. The difference in the average volume measure between positive and negative subsamples increases substantially during the

[26]For instance, see Pan and Poteshman (2006), Roll et al. (2010), Johnson and So (2012), and Ge et al. (2015).

days before negative news. The lower two panels of Figure 6 provide additional support for our hypothesis that informed trading takes place ahead of SCNs. It shows that the average ratio of OTM call to OTM put implied volatility does not differ significantly between the subsamples of positive and negative SCNs until around thirty to forty trading days ahead of the SCN. During the last weeks preceding the event, however, the measure increases significantly for the subsample of positive SCNs. This indicates that the pricing of call options, on average, increases relative to that of put options ahead of positive news. In contrast, the measure slightly decreases for the subsample of negative events, meaning that put options become relatively more expensive ahead of negative events.

In a next step, we examine whether the above patterns are different between the subsample of scheduled and unscheduled SCNs, and whether the differences are consistent with our predictions. We classify any event as scheduled that falls on a quarterly earnings announcement date. Figure 7 plots the difference between the average directional trading measures ahead of positive and negative events. The two measures of directional trading activity correspond to those plotted in Figure 6. We observe that the previously documented patterns exist in both subsamples. More importantly, we document that the increase in the difference of both measures between the subsample of positive and negative events increases sharply on the one to three days preceding a scheduled event. In contrast, this increase stretches over a longer time period ahead of unscheduled news. These observations are consistent with our hypotheses that informed investors trade (i) briefly ahead of scheduled events – despite potential run-ups in implied volatility ahead of these and (ii) further ahead of unscheduled events with uncertain timing.

The previous evidence supports our hypotheses that there is informed trading ahead of SCNs, and that patterns in informed trading are consistent with our predictions. However, it may also be due to a combination of sample selection and uninformed speculation. For instance, speculators might bet that firms approaching financial distress declare bankruptcy by acquiring put options. As our sample only includes the observations for which a news event, such as a bankruptcy, occurred, our previous results may suggest the prevalence of informed trading even in case there is only uninformed speculation. In the following, we address this concern by predicting SCNs in the aggregate cross-section of stocks.

Table 5 reports results from multinomial logistic regressions of an indicator whether (i) no, (ii) a negative, or (iii) a positive news event takes places over the next 1-3 days (columns 1 and 2) or the next 1-10 days (columns 3 and 4) on explanatory variables capturing trading activity in call and put options offering high expected returns to informed traders. The sample comprises all stock-days from 2000-2014 reported in the CRSP database that meet standard sample selection criteria, for which OptionMetrics data is available.

As opposed to the previous naive analysis, our explanatory variables are directly based on or theoretical framework. Relative call (put) volume is defined as the volume of call (put) options with high expected returns to informed trading scaled by total call (put) volume. Expected returns are computed using Equation 4 for call and put options for a private signal about a price jump of +10% and -10% anticipated for the next day (columns 1 and 2) or in ten days from now (columns 3 and 4). High expected returns returns are expected returns in the highest decile of the pooled distribution. Similarly, the relative call (put) implied volatility (Rel. Call IV or Rel. Put IV) is computed as the average implied volatility of call (put) options with high a expected return divided by that of all other options. On stock-days for which information about implied volatilities is missing even though options were traded, we set the value of Rel. Call IV (Rel. Call IV) equal to the average value of the pooled sample.

We indeed find that high pricing of or high trading volume in options offering the highest expected returns to informed investors predicts negative and positive SCNs in the aggregate cross-section. Consistent with the evidence presented previously, we show that the put option volume ratio predicts negative corporate news, while the call option IV ratio predicts positive corporate news. Using this approach, we can predict positive and negative news in the short term (over the next three trading days) and even over the next ten trading days.[27] These results cannot be explained by a potential sample selection bias and indicate that our

[27]The negative coefficient of the call volume measure in the fourth column is due to the fact that we compute the ten days measure

theoretical framework enables us to identify informed trading activity in the options market.

6. Conclusion

In this paper, we propose a framework for describing how informed investors can leverage their private information in the options market. We assume that their private signal includes information about the timing of future news events and their impact on stock prices. Since this information can be uncertain, the signal's quality influences the choice of option strategy enabling an informed investor to maximize his expected return. Furthermore, we account for bid-ask spreads and minimum option prices, and demonstrate that these market frictions can substantially affect the trading behaviour of insiders. Amongst others, our framework predicts that informed investors often trade ATM rather than OTM options.

We validate our framework in three different empirical analyses. First, we benchmark our predictions against illegal insider trades documented in a hand-collected sample of SEC litigation cases. Indeed, we report that characteristics of cases of actual insider trading are consistent with our predictions. In addition, we show that insider trading is concentrated in options that offer high expected returns to informed trading according to our framework.

In a second step, we use the comprehensive RavenPack news database to explain extreme price movements by news stories and create a sample of 30,975 significant corporate news from twelve different categories reported over the years 2000-2014. We then document that naive measures of directional trading in the options market behave differently ahead of positive versus negative news events, which indicates the presence of informed trading. Patterns in this suspicious trading activity are consistent with the trading behavior of informed investors predicted by our theoretical framework.

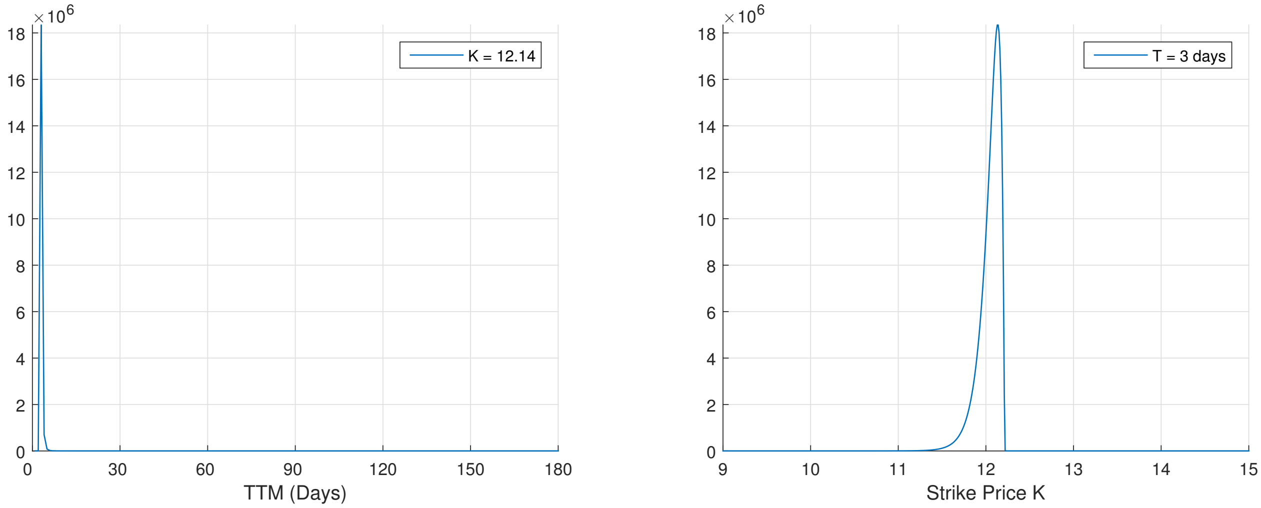
In a third step, we address concerns that the documented unusual trading activity is due to speculation rather than informed trading. We do so by showing that measures capturing trading activity in call (put)

assuming that events are expected to occur in ten days, where as the dependent variable in our regression flags events over the next ten rather than in ten days.

options with high expected returns computed using our framework predict significant positive (negative) corporate news in the aggregate cross-section of stocks.

In sum, this paper provides a framework allowing to identify the option strategy that maximizes returns to informed trading. Our approach can be applied to (i) help regulators detect illegal insider trading (ii) provide guidance to (legally) informed investors on how to leverage their private information, and (iii) extract information from the options market that enables the prediction of corporate events and stock returns.

(a) Zero bid-ask spread and no minimum price, no IV run-up



(b) Market frictions and IV run-up

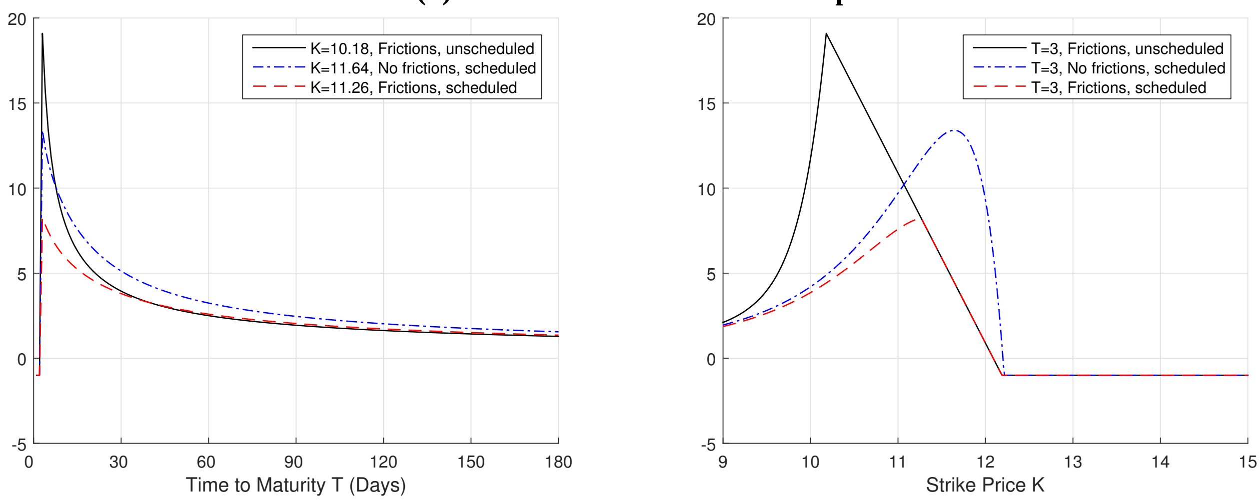
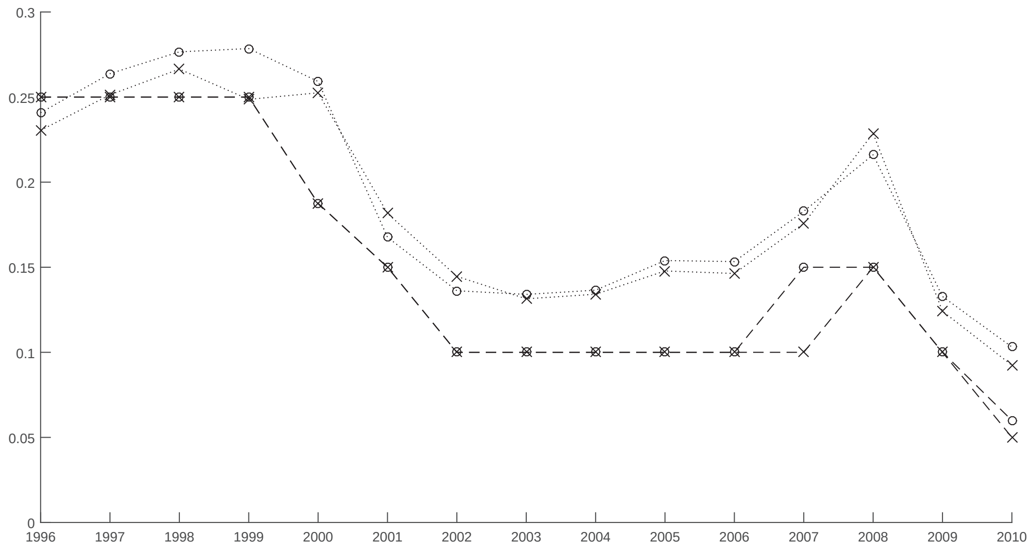
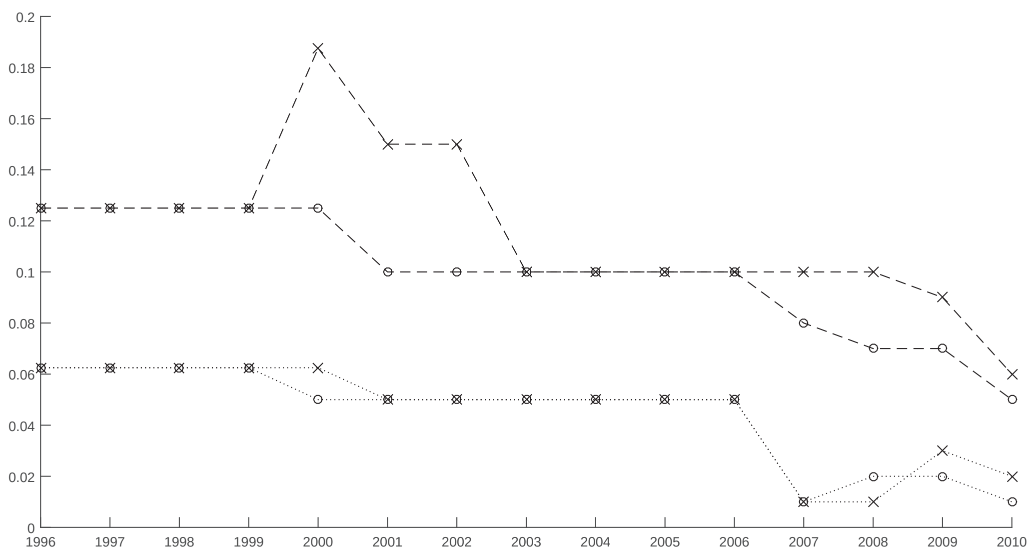


Figure 1: The Effect of Market Frictions and Run-Ups in Implied Volatility on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The upper two graphs are based on the assumption that there are neither market frictions nor a run-up in implied volatility . The bid-ask spread and the minimum price are equal to zero. The lines in the two lower graphs that are labelled "market frictions" assume a bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining equal. The lines labelled "scheduled" assume a Dubinsky and Johannes (2006) run-up in implied volatility ahead of the event. On each side, the strike price (maturity) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima in the left and the right graphs are identical. The timing and magnitude of the news-induced jump are known with certainty (κ=.2, Δ_t=3/360, σ_κ=0, $\sigma_{\Delta t}$=0), and S_0=10, r=.03, σ=.4.



(a) Panel A



(b) Panel B

Figure 2: Time Series of Bid-Ask Spreads and the Lowest Prices of Equity Options:
Panel A plots the evolution of the average (dotted line) and median (dashed line) of bid-ask spreads. Averages and medians are computed over all contract-days with a trading volume of at least 100 options and non-negative bid-ask spreads. *Panel B* displays the evolution of the minimum (dotted line) and the first percentile (dashed line) of option prices below three dollars. Minima and percentiles are computed over all contract-days with a trading volume of at least 100 options. Circles mark call options, crosses mark put options.

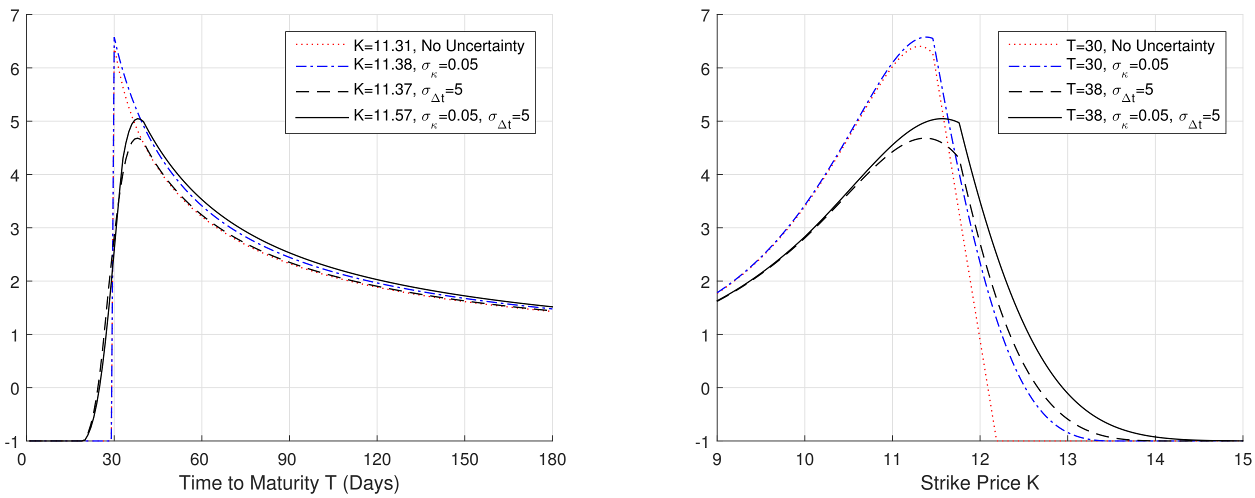


Figure 3: The Effect of Noise in the Private Signal on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The left (right) graph plots expected returns as a function of the time to maturity (strike price) of the option. On each side, the strike price (maturity) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima of each function in the left and the right graph are identical. In each graph, the four lines represent the case of no uncertainty (red dots), uncertainty about the event's effect on the stock price $\sigma_\kappa > 0$ (blue dash-dots) uncertainty about the time to announcement $\sigma_{\Delta t} > 0$ (dashed black line), and uncertainty in both dimensions (solid black line). Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Furthermore, κ=.2, Δ_t=30/360, S_0=10, r=.03, σ=.4.

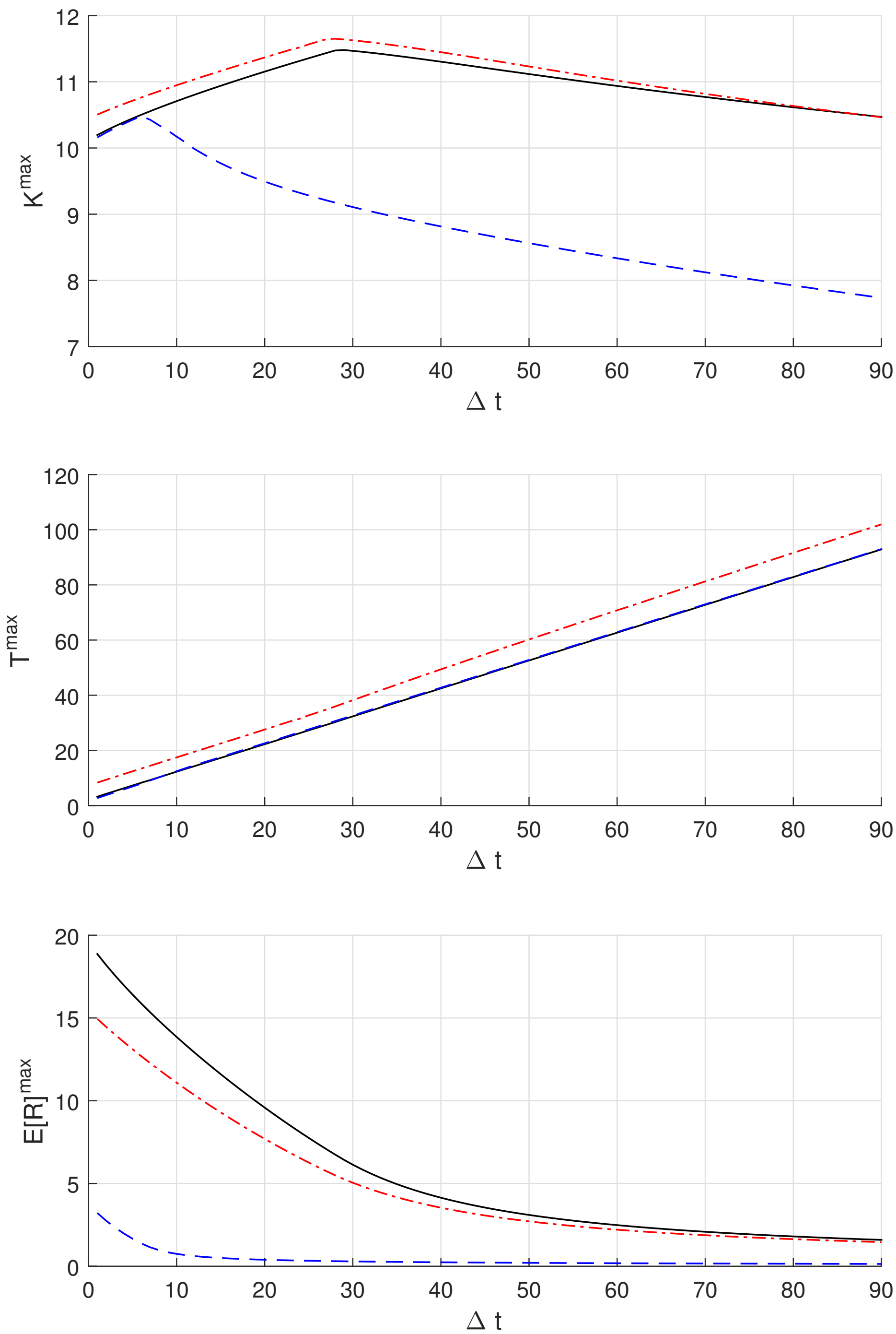


Figure 4: Maximizing Expected Returns to Informed Trading in *Call Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5\ days$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

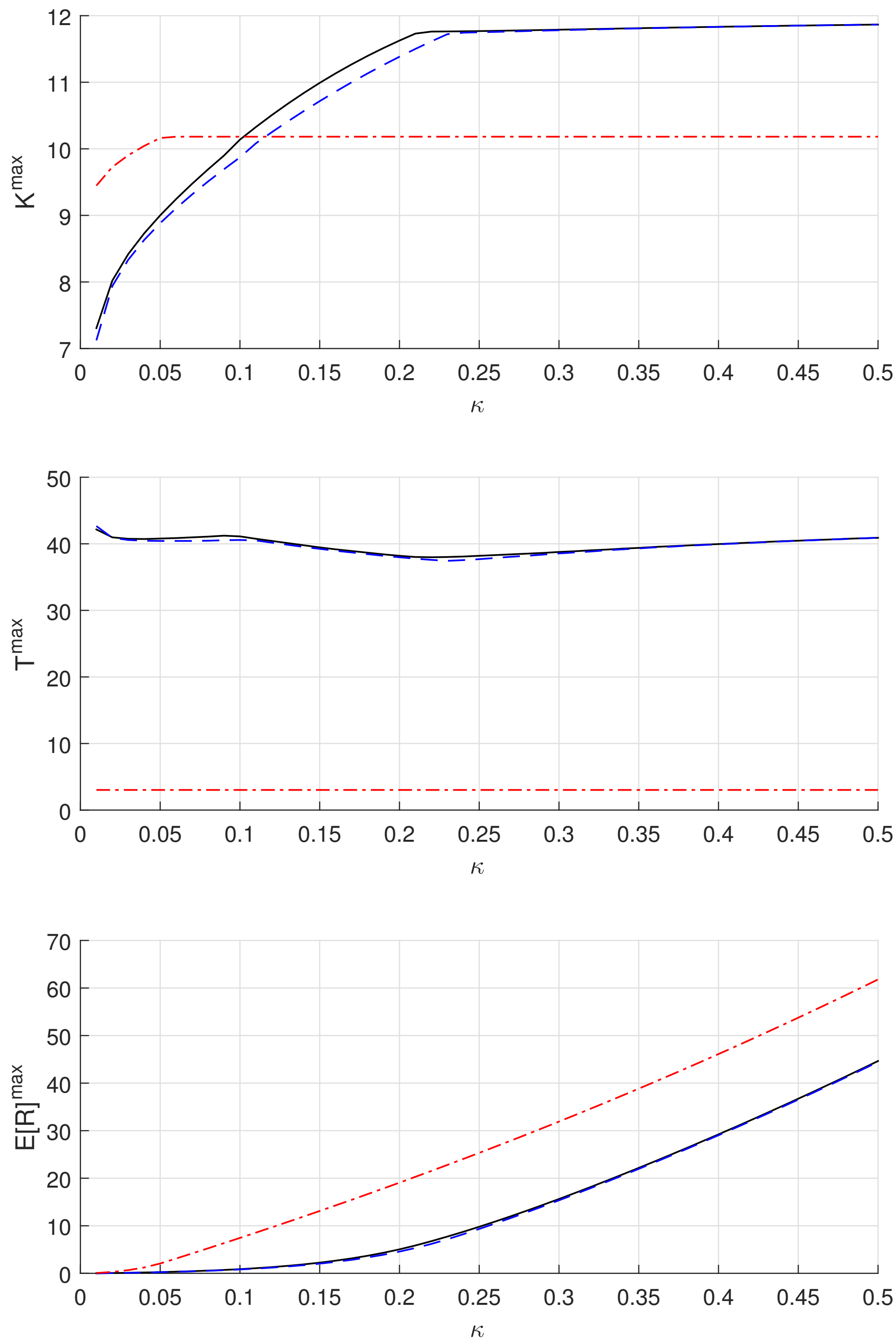


Figure 5: Maximizing Expected Returns to Informed Trading in *Call Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ $days$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ $days$, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0$ $days$, $\sigma_\kappa 0.005$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

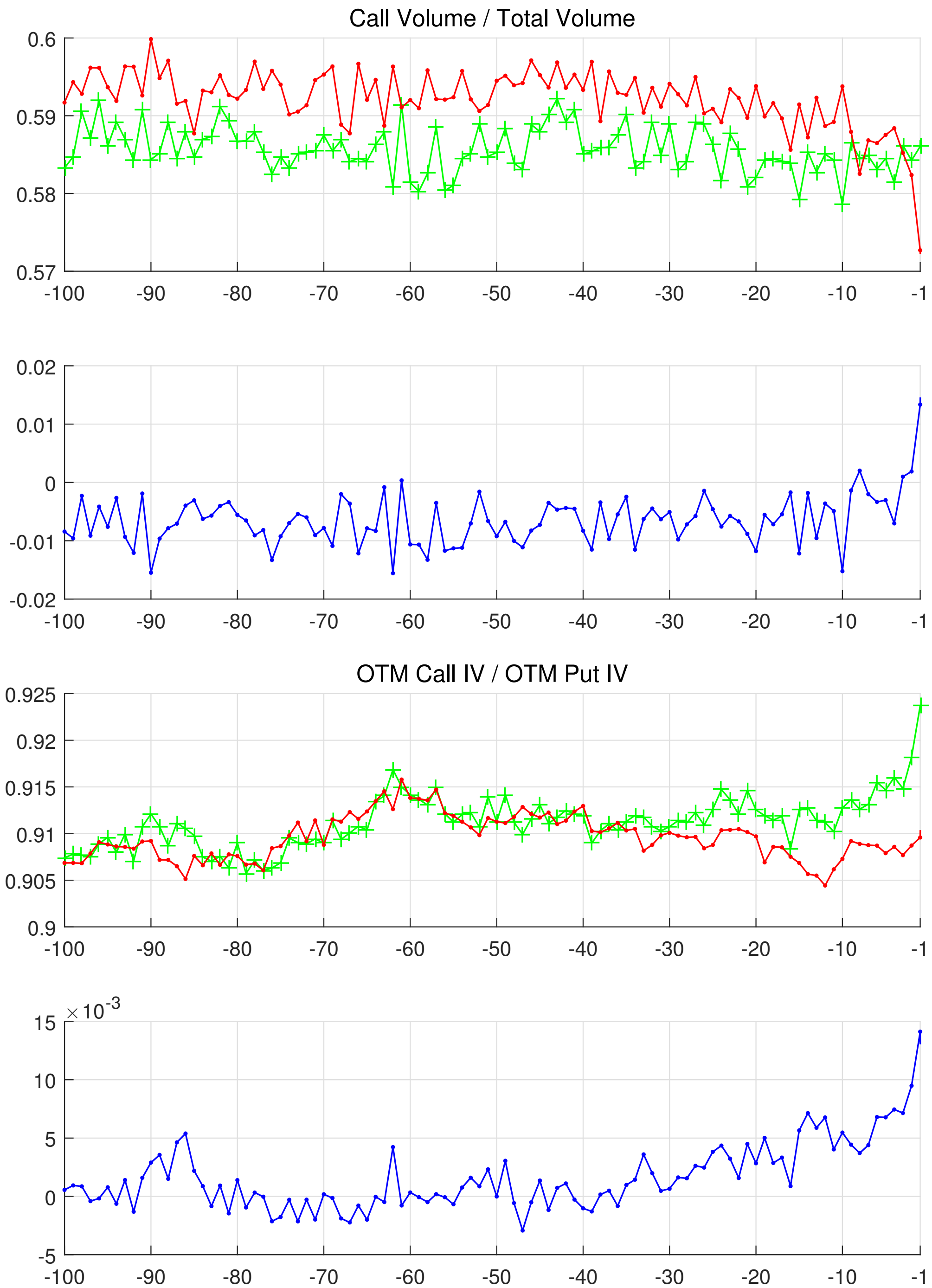


Figure 6: Suspicious Trading Activity ahead of News Events:

This figure plots the average directional trading activity ahead of positive and negative events (first and third graph), as well as the difference between the two (second and fourth graph). The two measures of directional trading activity are the ratio of call volume to total option volume (first two graphs) and the implied volatility of OTM call options to that of OTM put options (last two graphs). The X-axis shows trading days relative to the event and does not include the day of the event itself.

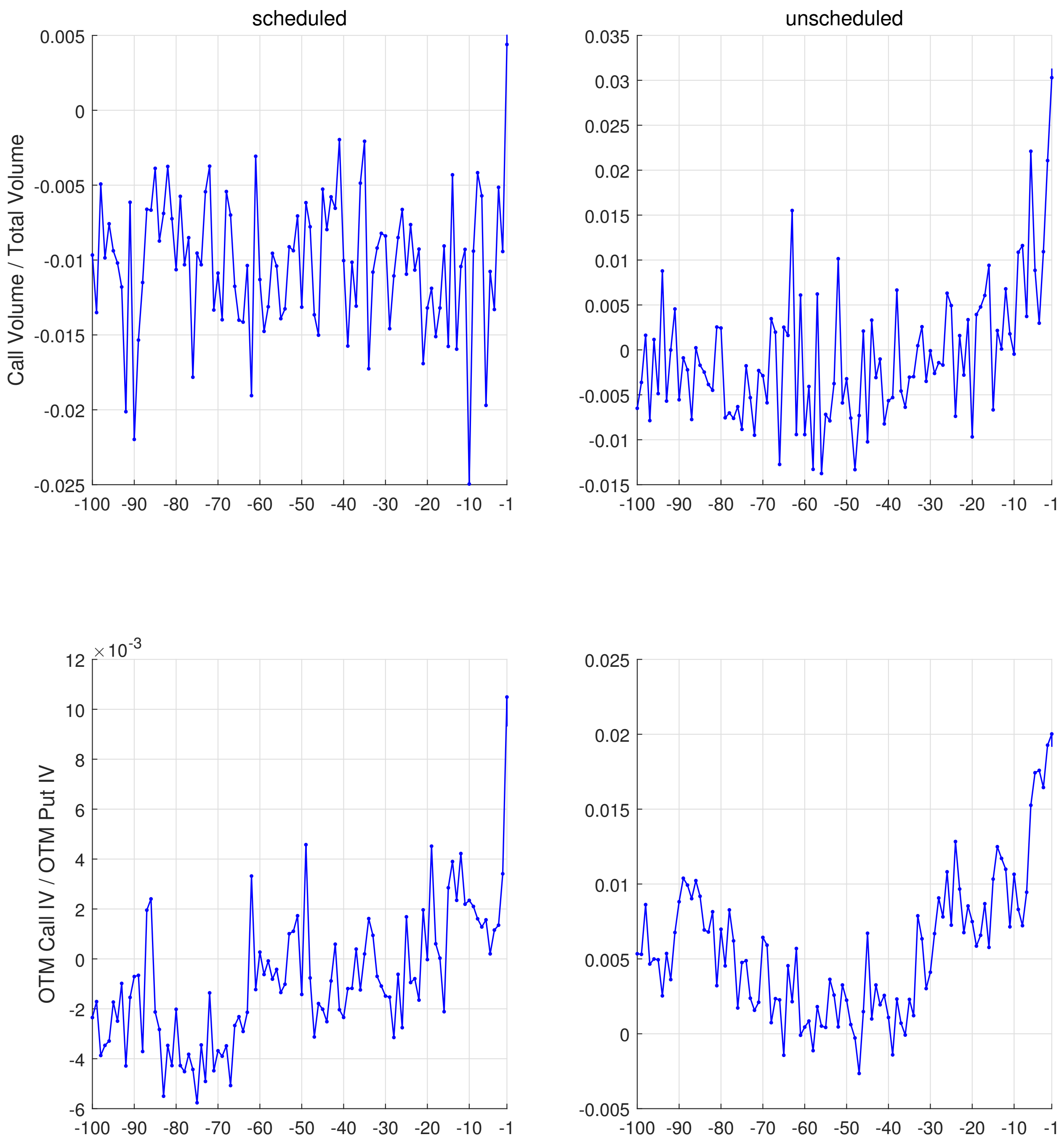


Figure 7: Suspicious Trading Activity ahead of Scheduled and Unscheduled Events:
This figure plots the difference between the average directional trading activity ahead of positive and negative events. The two measures of directional trading activity are the ratio of call volume to total option volume (upper graphs) and the implied volatility of OTM call options to that of OTM put options (lower graphs). The left (right) graphs plot these measures for the subsample of scheduled (unscheduled) news, which we define as any news (not) published at the time of a quarterly earnings announcement. The X-axis shows trading days relative to the event and does not include the day of the event itself.

Table 1: *SEC Litigation Cases - Summary Statistics.*
This table reports descriptive statistics for our sample of SEC litigation cases on insider trading in option markets ahead of earnings and M&A announcements. The sample is restricted to trades that we were able to match to specific option contracts in the OptionMetrics database. Option prices are end-of-day midpoints. Option returns are the ratio of the option's first available end-of-day bid price after the announcement date and the end-of-day best ask on the purchase date minus one. If an option was not traded within the month following the announcement, we use its intrinsic value the day following the announcement as a numerator instead of the bid price. Inside Options is the number of options traded by the insider, Inside Opt./ Total Vlm. scales this number by the total volume traded in the contract on the same day. Reported are average, standard deviation, and the 5th, 50th and 95th percentile.

		ALL	*Earnings (Calls)*	*Earnings (Puts)*	*M&A (Calls)*
Number of events		148.00	13.00	29.00	109.00
Number of option days		358.00	16.00	58.00	284.00
Nb. Calls(%)		83.80	100.00	0.00	100.00
Nb. Puts(%)		16.20	0.00	100.00	0.00
S/K * 100	*Avg.*	96.84	104.72	90.67	97.65
	Std.	14.67	13.84	16.65	13.91
	5*th*	76.77	77.04	53.36	79.12
	50*th*	94.60	104.21	96.33	93.90
	95*th*	123.88	123.18	107.99	125.31
Time to Mat.	*Avg.*	46.40	33.31	38.28	48.79
	Std.	37.82	18.61	39.96	37.89
	5*th*	8.00	6.50	3.00	9.00
	50*th*	36.00	29.00	24.50	38.00
	95*th*	130.00	68.10	116.20	135.30
Option Price	*Avg.*	1.49	3.05	2.77	1.14
	Std.	1.79	2.84	2.94	1.13
	5*th*	0.20	0.61	0.36	0.20
	50*th*	0.95	1.90	1.45	0.80
	95*th*	4.46	9.78	9.84	3.03
Bid-Ask	*Avg.*	0.20	0.21	0.23	0.19
	Std.	0.21	0.15	0.20	0.21
	5*th*	0.05	0.07	0.05	0.05
	50*th*	0.15	0.18	0.15	0.15
	95*th*	0.50	0.50	0.75	0.46
Option Ret [%]	*Avg.*	1,135.58	109.89	473.05	1,328.68
Stock Ret [%]	*Avg.*	19.10	4.65	−22.60	28.43
delta T (days)	*Avg.*	17.47	8.56	12.41	19.01
Inside Options	*Avg.*	381.52	911.13	244.86	379.59
Inside Opt./ Total Vlm. [%]	*Avg.*	1.17	0.5	0.51	1.42
Imp. Vol. [%]	*Avg.*	0.50	0.66	0.61	0.47
Delta	*Avg.*	0.24	0.60	−0.46	0.36

Table 2: *Predicting SEC Litigated Option Contracts.*
This table reports results from logit regression of an indicator whether – according to the SEC Litigation files – an insider traded in a specific option contract or not. For each day on which an option written on a stock was traded by an insider we include all options written on the same stock that traded on this day. The dependent variable flags the option traded by the insider and equals one for all 358 observations in our SEC litigation sample. Explanatory variables include the percentile rank of expected returns ($\mathbb{E}[R]$ Rank) and the Acharya and Johnson (2010) "bang for the buck" measure. Standard errors are reported in parentheses.

	(1)	(2)	(3)
(Intercept)	-0.027^a	0.096^a	-0.035^a
	(0.013)	(0.007)	(0.013)
$\mathbb{E}[R]$ Rank	0.269^a		0.249^a
	(0.021)		(0.021)
$\delta S/C$		5.548^a	4.315^a
		(0.685)	(0.675)
R^2	0.058	0.023	0.072

[a] Statistically significant at the one percent level, respectively.

Table 3: *Significant Corporate News - Descriptive Statistics*
This table reports descriptive statistics for the sample of positive and negative news events for each of the categories to which we assign news in our sample. Displayed are the number of observations N, the percentage of observations that fall on an earnings announcement day and are thus classified as scheduled (%EAD), the average, median, and standard deviation of returns, as well as the percentage of observations for which the relative trading volume (defined as the number of shares traded on a given day scaled by the number of shares outstanding) is above the 90th percentile of a stock's distribution of this measure.

Positive News			Return			
	N	% EAD	Avg.	Median	Std. Dev.	%High Vlm.
Acquisition (Acquirer)	552	27.90	11.42	9.88	6.99	87.14
Acquisition (Target)	780	13.59	24.98	21.61	16.63	99.36
Analyst	3,606	43.93	12.44	10.27	8.74	89.24
Business Contract	653	11.94	13.47	10.69	9.78	79.02
Credit Rating	124	19.35	12.79	9.66	9.11	95.97
Drug & Product Development	103	13.59	13.62	10.42	12.85	83.50
Dividends	165	13.33	8.25	6.97	4.56	76.36
Earnings	7,412	100.00	11.33	9.92	6.28	90.21
Financing	338	55.92	8.96	7.73	5.09	84.32
Guidance	901	59.82	11.20	9.74	7.19	91.45
Management Change	305	7.21	10.58	8.13	12.10	69.18
Merger	71	19.72	12.42	11.06	8.08	92.96
Others	201	24.88	14.31	11.71	10.32	88.06
ALL	15,211	69.30	11.73	9.98	7.47	89.59
No Associated News	25,881	12.24	10.57	8.71	7.75	63.12

Negative News			Return			
	N	% EAD	Avg.	Median	Std. Dev.	%High Vlm.
Acquisition (Acquirer)	161	8.07	−10.03	−8.73	6.47	84.47
Acquisition (Target)	0	0.00	0.00	0.00	0.00	0.00
Analyst	5,732	53.02	−15.74	−12.54	11.17	94.78
Business Contract	0	0.00	0.00	0.00	0.00	0.00
Credit Rating	189	33.86	−15.08	−11.40	13.33	91.53
Drug & Product Development	54	16.67	−22.62	−18.90	14.70	94.44
Dividends	0	0.00	0.00	0.00	0.00	0.00
Earnings	6,918	100.00	−11.15	−9.30	6.78	91.15
Financing	265	18.49	−10.30	−9.23	5.87	87.92
Guidance	1,970	61.37	−13.73	−11.43	8.79	94.87
Management Change	240	35.83	−13.33	−9.69	11.48	87.92
Merger	64	18.75	−10.78	−8.20	7.95	95.31
Others	171	14.04	−13.73	−11.18	9.66	87.72
ALL	15,764	72.46	−13.26	−10.82	8.83	92.76
No Associated News	26,797	11.05	−9.56	−7.93	6.41	61.35

Table 4: *Expected Returns to Informed Trading Ahead of News*
This table reports medians ("50") and the 90th percentile ("90") of expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category covered in our sample. Expected returns are computed using Equation 4, assuming that informed investors trade ten days ahead of unscheduled news and one day ahead of scheduled news. The anticipated stock price reaction and its uncertainty are equal to the average and standard deviation of the return in each category, as reported in Table 3.

Positive News	Scheduled		Unscheduled	
	50	90	50	90
Acquisition (Acquirer)	114.72	472.63	92.53	318.60
Acquisition (Target)	293.14	1,289.50	319.90	1,402.91
Analyst	120.15	520.21	103.83	445.07
Business Contract	112.41	574.18	97.78	481.05
Credit Rating	106.90	472.10	141.73	647.44
Drug & Product Development	173.20	1,217.68	124.11	710.38
Dividends	83.71	274.23	67.16	269.00
Earnings	110.95	421.29		
Financing	113.57	506.83	77.25	322.79
Guidance	139.53	557.57	95.17	403.54
Management Change	109.85	666.02	91.08	463.08
Merger	151.56	522.61	99.59	596.22
Others	155.92	619.20	112.79	669.61
ALL	115.86	465.54	110.68	553.15

Negative News	Scheduled		Unscheduled	
	50	90	50	90
Acquisition (Acquirer)	100.39	318.44	60.94	269.77
Analyst	118.96	497.72	95.18	463.94
Credit Rating	83.61	564.13	65.84	396.46
Drug & Product Development	69.27	233.43	88.80	367.66
Earnings	101.63	363.57		
Financing	37.60	152.56	45.99	177.87
Guidance	149.81	688.08	84.24	398.10
Management Change	125.38	481.19	87.82	465.75
Merger	46.88	308.97	105.46	417.90
Others	126.48	920.75	75.25	392.01
ALL	111.29	442.55	86.72	425.46

Table 5: *Predicting Significant News.*

This table reports results from multinomial logistic regressions of an indicator whether (i) no, (ii) a negative, or (iii) a positive news event takes places over the next 1-3 days (columns 1 and 2) or the next 1-10 days (columns 3 and 4) on explanatory variables capturing trading activity in call and put options offering high expected returns to informed traders. The reference case is the one without news, coefficients for negative (positive) events are reported in columns 1 and 3 (2 and 4). The sample comprises all stock-days reported in the CRSP database over the years 2000-2014 that are common stocks with a minimum stock price of USD 5, a market value of more than USD 10mio with positive trading volume and for which contract specific call and put volume data from are available from the OptionMetrics database. Relative call (put) volume is defined as the volume of call (put) options with high expected returns to informed trading scaled by total call (put) volume. Expected returns are computed for call and put options for a private signal about a price jump of +10% and -10% anticipated for the next day (columns 1 and 2) or in ten days from now (columns 3 and 4). High expected returns returns are expected returns in the highest decile of the pooled distribution. Similarly, the relative call (put) implied volatility (Rel. Call IV or Rel. Put IV) is computed as the average implied volatility of call (put) options with high a expected return divided by that of all other options. On stock-days for which information about implied volatilities is missing even though options were traded, we set the value of Rel. Call IV (Rel. Call IV) equal to the average value of the pooled sample. Standard errors are reported in parentheses.

	Short-Term		Mid-Term	
	Neg.	Pos.	Neg.	Pos.
(Intercept)	-5.46^{a}	-5.76^{a}	-4.31^{a}	-4.97^{a}
	(0.24)	(0.24)	(0.16)	(0.15)
Rel. Call Vlm	0.00	−0.16	0.06	-0.16^{a}
	(0.10)	(0.11)	(0.05)	(0.05)
Rel. Put Vlm	0.33^{a}	0.06	0.19^{a}	0.03
	(0.11)	(0.12)	(0.05)	(0.05)
Rel. Call IV	−0.04	0.34^{b}	0.22	0.68^{a}
	(0.20)	(0.18)	(0.15)	(0.14)
Rel. Put IV	−0.06	−0.04	-0.25^{c}	0.10
	(0.19)	(0.20)	(0.14)	(0.13)
	626,874	626,874	626,874	626,874

^{a,b,c} Statistically significant at the one, five, or ten percent level, respectively.

Appendix

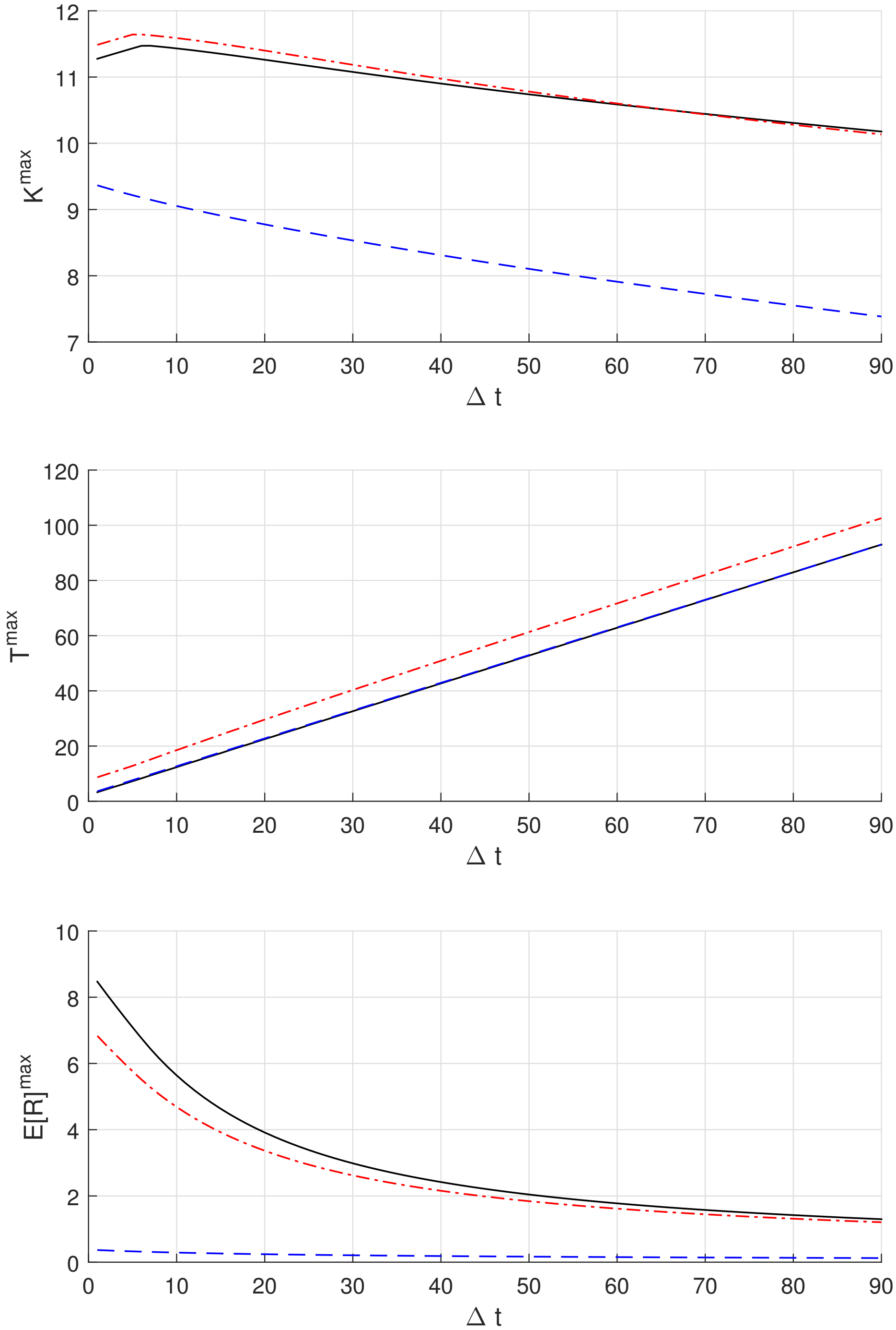


Figure A1: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t}$ = 1 *day*, κ = 0.2, σ_κ0.05
(2) blue dashed line: $\sigma_{\Delta t}$ = 1 *day*, κ = 0.05, σ_κ0.05
(3) red dash-dotted line: $\sigma_{\Delta t}$ = 5 *days*, κ = 0.2, σ_κ0.05
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are scheduled, meaning that there is a run-up in implied volatilities preceding the event.

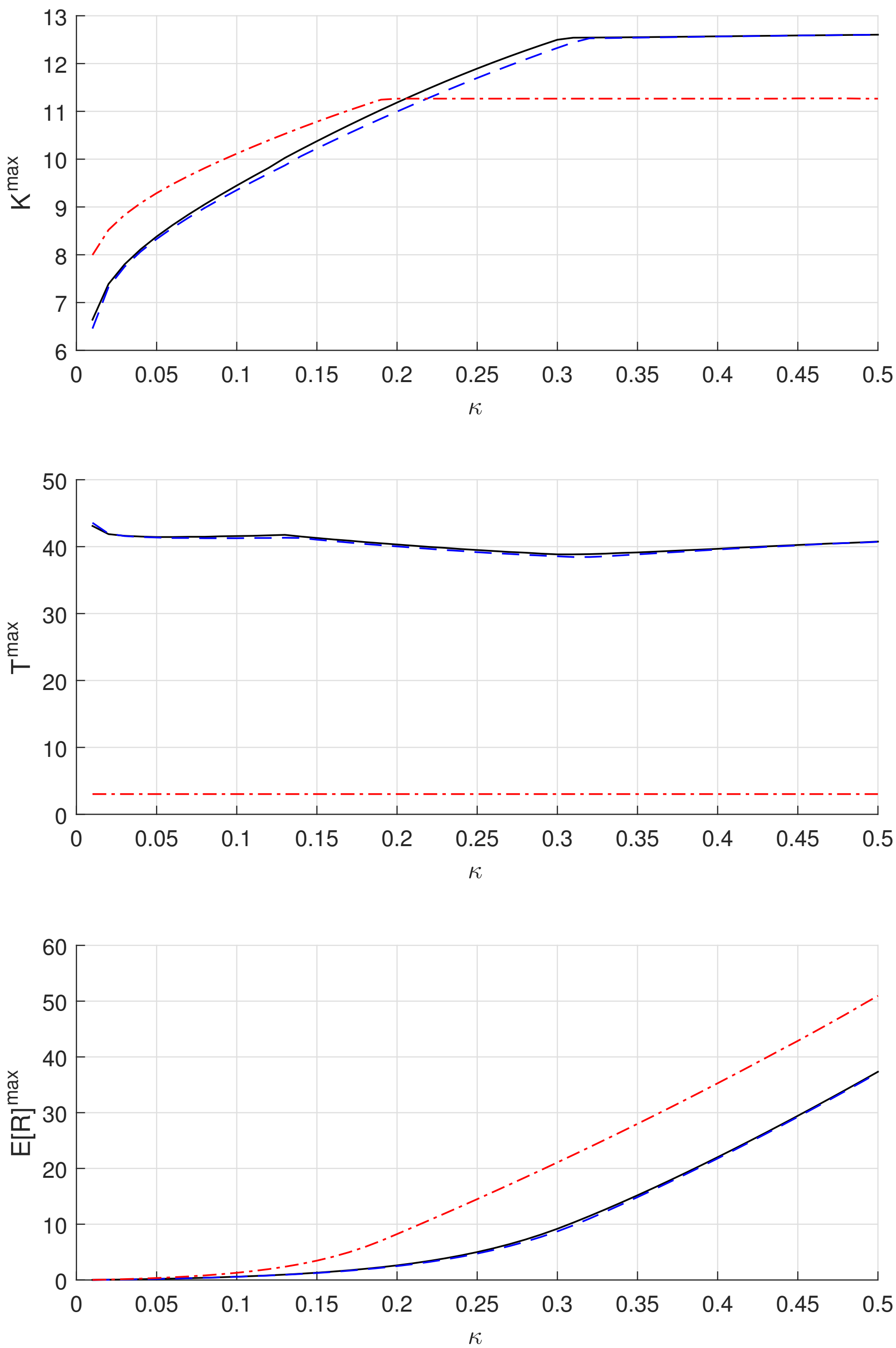


Figure A2: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_\kappa 0.005$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are scheduled, meaning that there is a run-up in implied volatilities preceding the event.

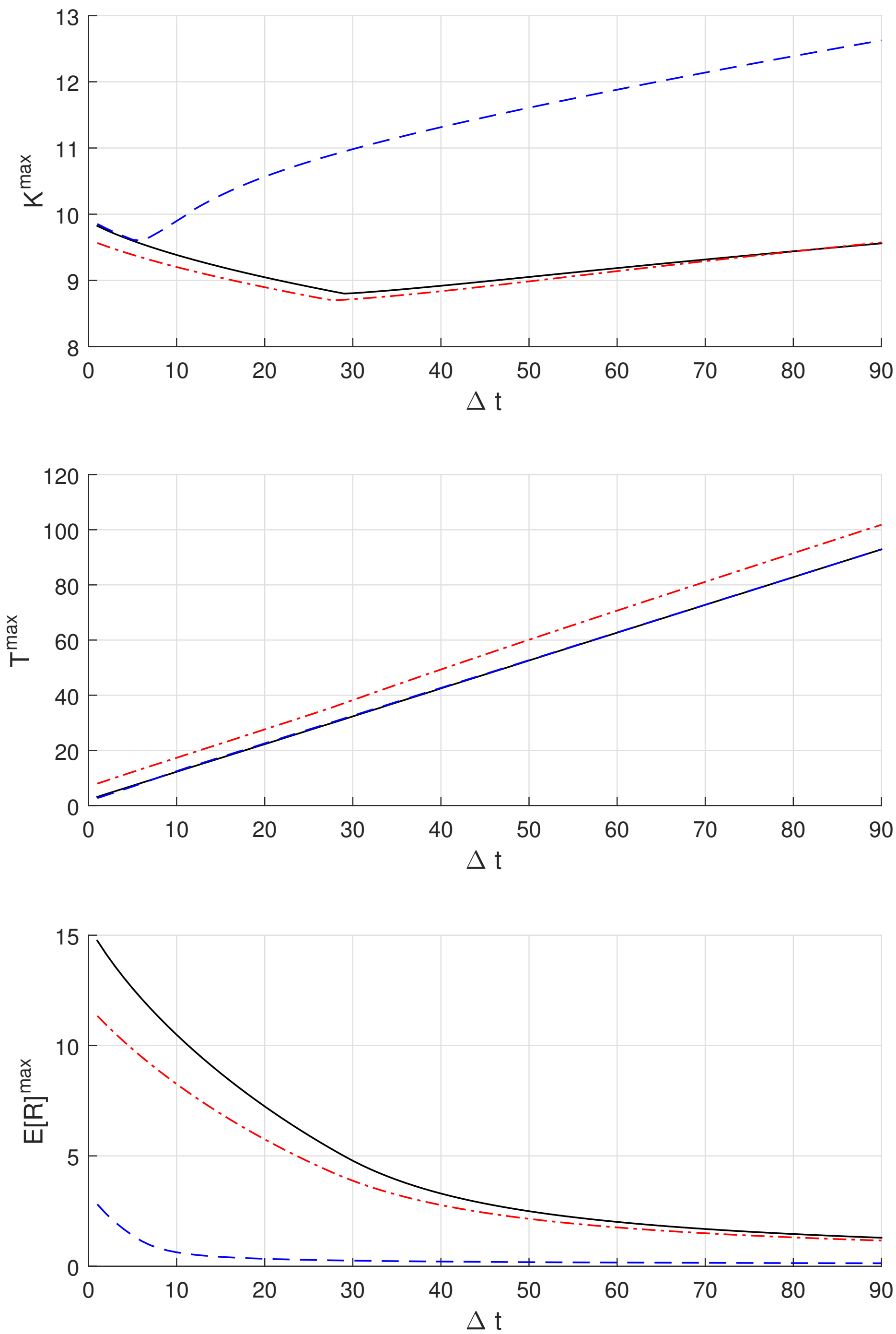


Figure A3: Maximizing Expected Returns to Informed Trading in *Put Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t}$ = 1 *day*, $\kappa = -0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t}$ = 1 *day*, $\kappa = -0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t}$ = 5 *days*, $\kappa = -0.2$, $\sigma_\kappa 0.05$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

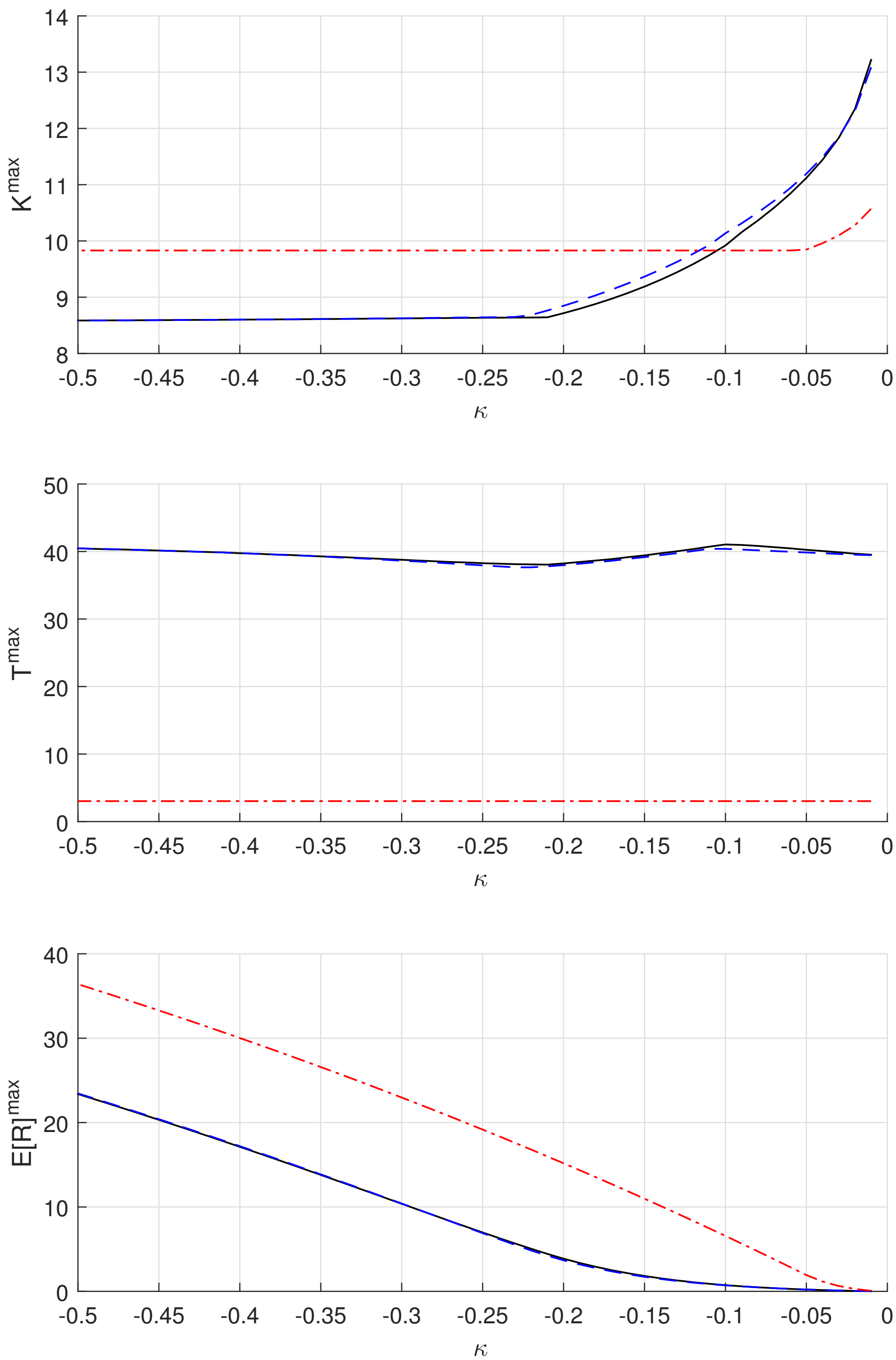


Figure A4: Maximizing Expected Returns to Informed Trading in *Put Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.

(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ *days*, $\sigma_\kappa 0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ *days*, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0$ *days*, $\sigma_\kappa 0.005$

In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

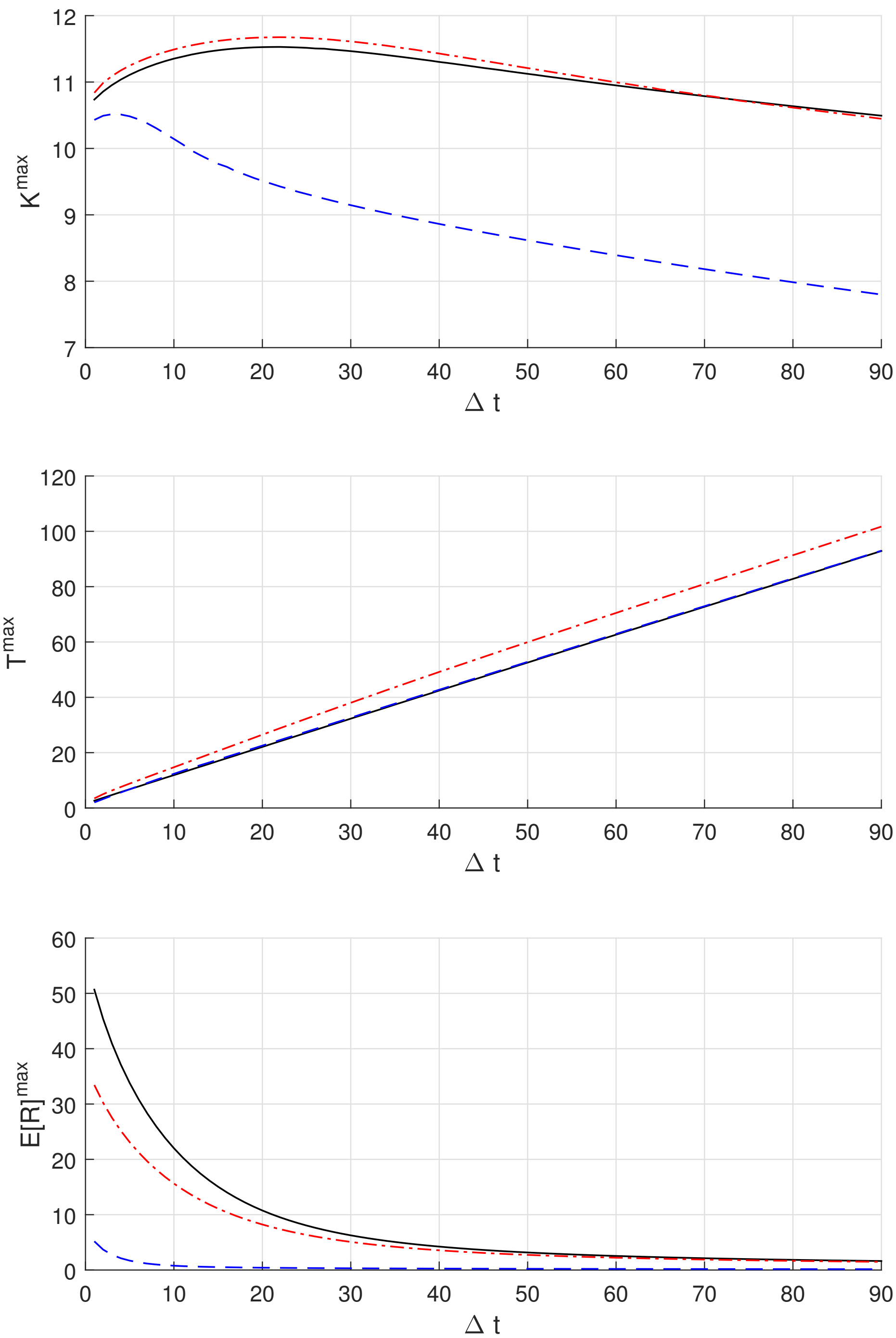


Figure A5: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t}$ = 1 *day*, κ = 0.2, σ_κ0.05
(2) blue dashed line: $\sigma_{\Delta t}$ = 1 *day*, κ = 0.05, σ_κ0.05
(3) red dash-dotted line: $\sigma_{\Delta t}$ = 5 *days*, κ = 0.2, σ_κ0.05
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

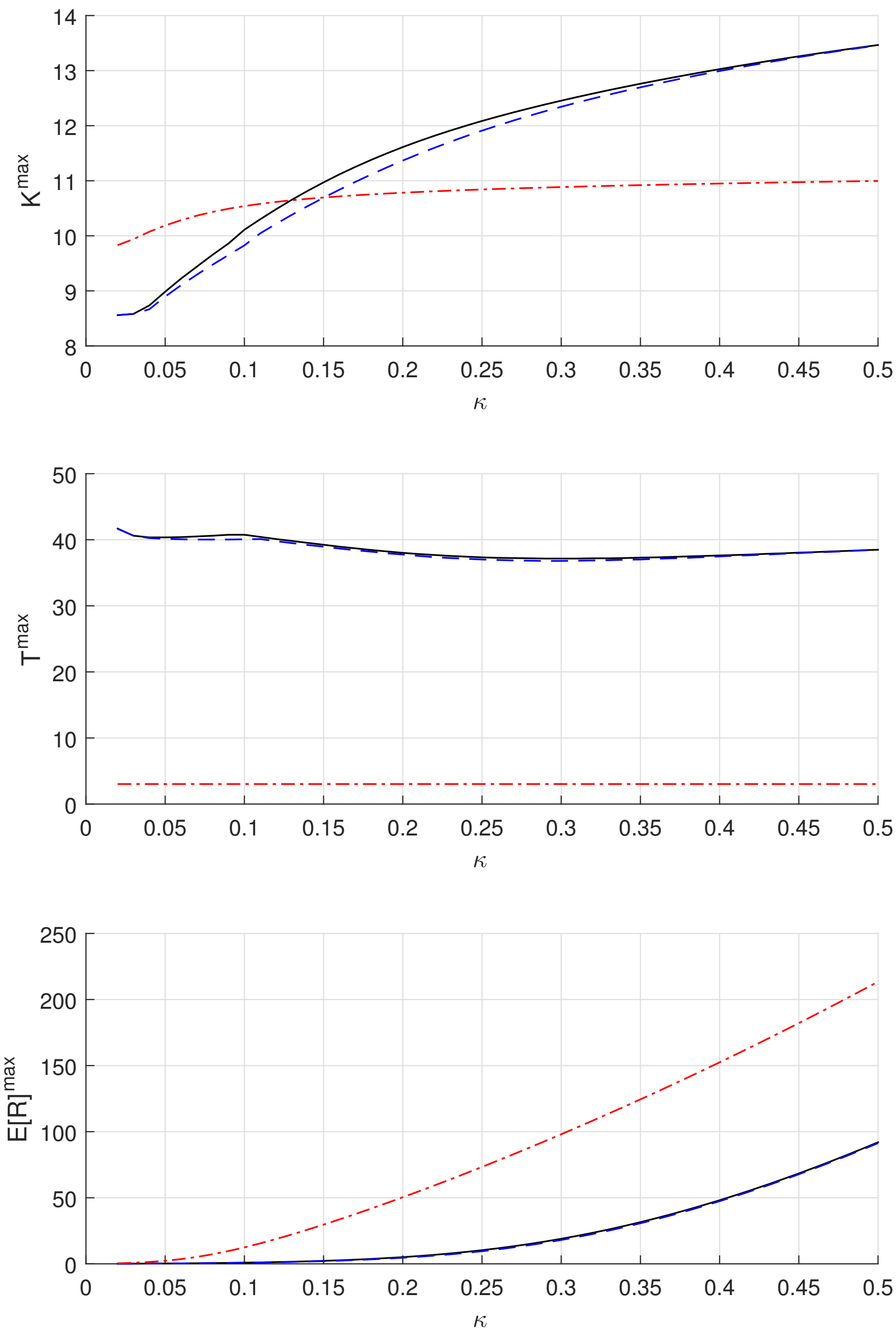


Figure A6: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_{\kappa}0.005$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

Table A1: *Odds Ratios of News Categories for Positive EPMs*

This table reports results from logistic regressions of an indicator of positive EPMs on variables indicating Ravepack news categories. The sample includes all stock-days in CRSP between 2000 and 2014 with a stock price of at least five dollars, a market capitalization of at least ten million dollars and is restricted to stocks for which we observe news in the Ravenpack database at least once. We observe 62,913 positive EPMs on 11.4 million stock days. For a given stock-day, a news indicator is set equal to one if news in that category were reported for the stock between 4pm on the previous trading date and 4pm of the given day. Of 527 Ravenpack categories for corporate news, we ignore all categories for which not a single news observation is made on a positive EPM day and include indicator variables for all 94 remaining categories. This table only reports statistics for indicator variables that are significant at the one percent level. To account for multiple hypothesis testing we use Bonferroni adjusted p-values, implying a minimum t-value of 4.12. The "Assigned Category" is the less granular definition of news category used in the primary analysis. Odds ratios are computed as the exponential of regression coefficients. N_{reg} is the number of news occurrences in the regression, that is, the sum of the indicator variable. N_{final} equals the number of news events of a given category that are used in the main analysis.

Ravenpack Category	Assigned Category	Beta	Odds Ratio	t-value	N_{reg}	N_{final}
acquisition-acquirer	Acquisition (Acquirer)	1.09	2.98	29.48	1365	552
acquisition-acquiree	Acquisition (Target)	3.39	29.80	74.48	1687	668
acquisition-interest-acquiree	Acquisition (Target)	2.47	11.85	25.28	264	112
analyst-ratings-change-positive	Analyst	2.57	13.13	134.13	4313	3,281
analyst-ratings-history-neutral	Analyst	0.52	1.68	5.56	159	23
analyst-ratings-set-positive	Analyst	0.78	2.19	15.73	435	269
price-target-upgrade	Analyst	0.67	1.96	4.92	106	33
business-contract	Business Contract	0.59	1.80	20.48	2368	653
credit-rating-unchanged	Credit Rating	0.56	1.76	5.11	124	37
credit-rating-watch-negative	Credit Rating	1.49	4.44	14.58	198	87
dividend	Dividends	0.36	1.43	9.03	1199	142
dividend-up	Dividends	0.35	1.42	5.52	414	23
regulatory-product-approval-granted	Drug & Product Development	1.06	2.89	12.32	224	103
conference-call	Earnings	0.33	1.39	8.65	1199	210
earnings	Earnings	0.48	1.62	22.29	12532	315
earnings-down	Earnings	0.39	1.48	9.99	1173	105
earnings-per-share-above-expectations	Earnings	1.14	3.14	39.25	3694	2,293
earnings-per-share-below-expectations	Earnings	0.61	1.84	14.41	1082	568
earnings-per-share-positive	Earnings	0.53	1.71	21.11	6394	316
earnings-positive	Earnings	0.63	1.88	22.63	4007	2,222
earnings-up	Earnings	0.53	1.70	19.00	3517	259
revenue-above-expectations	Earnings	0.52	1.69	17.88	3679	93
revenues	Earnings	0.54	1.72	19.62	5093	877
revenue-up	Earnings	0.50	1.64	16.11	2551	134
same-store-sales-up	Earnings	0.35	1.43	6.73	681	20
buybacks	Financing	0.64	1.90	14.09	851	338
earnings-guidance-up	Guidance	0.76	2.15	19.85	1279	643
earnings-per-share-guidance	Guidance	0.36	1.44	13.94	3257	95
ebitda-guidance	Guidance	0.41	1.50	4.19	142	11
revenue-guidance	Guidance	0.27	1.31	10.13	2771	75
revenue-guidance-up	Guidance	0.37	1.45	11.05	1537	77
executive-appointment	Management Change	0.17	1.19	4.86	1649	305
merger	Merger	1.15	3.15	14.17	444	71
regulatory-investigation	Others	1.20	3.32	13.79	254	40
settlement	Others	0.50	1.66	4.39	138	39
stake-acquiree	Others	1.52	4.59	15.07	152	82
stock-splits	Others	1.31	3.69	11.44	144	40

Table A2: *Odds Ratios of News Categories for Negative EPMs*

This table reports results from logistic regressions of an indicator of negative EPMs on variables indicating Ravepack news categories. The sample includes all stock-days in CRSP between 2000 and 2014 with a stock price of at least five dollars, a market capitalization of at least ten million dollars and is restricted to stocks for which we observe news in the Ravenpack database at least once. We observe 63,565 negative EPMs on 11.4 million stock days. For a given stock-day, a news indicator is set equal to one if news in that category were reported for the stock between 4pm on the previous trading date and 4pm of the given day. Of 527 Ravenpack categories for corporate news, we ignore all categories for which not a single news observation is made on a negative EPM day and include indicator variables for all 95 remaining categories. This table only reports statistics for indicator variables that are significant at the one percent level. To account for multiple hypothesis testing we use Bonferroni adjusted p-values, implying a minimum t-value of 4.12. The "Assigned Category" is the less granular definition of news category used in the primary analysis. Odds ratios are computed as the exponential of regression coefficients. N_{reg} is the number of news occurrences in the regression, that is, the sum of the indicator variable. N_{final} equals the number of news events of a given category that are used in the main analysis.

Ravenpack Category	Assigned Category	Beta	Odds Ratio	t-value	N_{reg}	N_{final}
acquisition-acquirer	Acquisition (Acquirer)	0.47	1.60	9.24	720	161
analyst-ratings-change-negative	Analyst	2.94	18.86	186.73	9,181	5,667
analyst-ratings-history-neutral	Analyst	0.53	1.70	4.55	108	18
analyst-ratings-history-positive	Analyst	0.53	1.69	10.45	693	21
price-target-downgrade	Analyst	1.21	3.35	7.99	107	26
credit-rating-downgrade	Credit Rating	0.78	2.18	8.98	230	78
credit-rating-unchanged	Credit Rating	0.70	2.01	6.20	119	48
credit-rating-watch-negative	Credit Rating	1.17	3.23	10.59	152	63
clinical-trials	Drug & Product Development	1.83	6.22	16.70	161	54
conference-call	Earnings	0.43	1.54	11.83	1,375	252
earnings	Earnings	0.64	1.90	29.45	14,101	2,663
earnings-below-expectations	Earnings	0.34	1.40	7.73	1,108	13
earnings-down	Earnings	0.52	1.69	15.59	1,997	160
earnings-negative	Earnings	0.38	1.46	8.23	1,119	27
earnings-per-share-above-expectations	Earnings	0.68	1.98	21.11	2,463	1,334
earnings-per-share-below-expectations	Earnings	0.87	2.38	23.77	1,892	927
earnings-per-share-meet-expectations	Earnings	0.92	2.52	9.62	147	66
earnings-per-share-negative	Earnings	0.58	1.79	14.80	1,620	112
earnings-per-share-positive	Earnings	0.25	1.28	9.74	5,999	46
earnings-positive	Earnings	0.58	1.79	20.83	3,893	611
earnings-up	Earnings	0.45	1.57	14.40	2,433	171
operating-earnings	Earnings	0.61	1.85	5.13	170	32
revenue-above-expectations	Earnings	0.52	1.68	17.16	3,213	48
revenue-below-expectations	Earnings	0.45	1.57	10.94	1,111	20
revenues	Earnings	0.52	1.69	19.26	5,579	248
revenue-up	Earnings	0.38	1.46	11.38	2,148	67
same-store-sales-down	Earnings	0.53	1.70	8.29	454	113
same-store-sales-up	Earnings	0.25	1.28	4.26	558	8
note-sale	Financing	0.80	2.22	9.78	304	116
public-offering	Financing	1.50	4.49	22.10	409	149
earnings-guidance	Guidance	0.88	2.40	24.13	1,583	544
earnings-guidance-down	Guidance	1.75	5.73	44.09	1,479	845
earnings-guidance-meet-expectations	Guidance	0.24	1.28	4.36	441	19
earnings-per-share-guidance	Guidance	0.50	1.65	19.85	3,858	176
revenue-guidance	Guidance	0.43	1.54	17.12	3,704	136
revenue-guidance-down	Guidance	0.66	1.93	13.19	804	214
revenue-guidance-up	Guidance	0.29	1.34	8.26	1,341	36
executive-resignation	Management Change	0.84	2.32	15.99	789	240
merger	Merger	0.79	2.20	7.14	170	64
layoffs	Others	0.35	1.41	4.29	251	26
legal-issues-defendant	Others	0.58	1.79	6.79	199	76
regulatory-investigation	Others	0.77	2.17	7.12	132	69

A. Implications of the Informed Trading Framework

This section presents a structured summary the most important predictions arising from the theoretical framework introduced in section 3. We describe how variations in the private information signals impact expected returns to informed trading and subsequently translate these into testable hypotheses.

(A) Predictions related to market frictions and pre event run-up in implied volatility:

1. *Impact on trading parameters:* Given market frictions, informed investors trade options that are near the money and avoid OTM and DOTM options, as these become prohibitively expensive in terms of their implied volatility. If an event is scheduled, the run-up in implied volatility ahead of the event adds to the cost of establishing any option strategy with positive vega and at the same time induces informed investors to decrease the moneyness of their position.
2. *Impact on expected returns:* Market frictions diminish expected returns by several orders of magnitude. Run-ups in implied volatility ahead of scheduled events add to this effect.
3. *Variations in the impact of market frictions:* The impact of market frictions on insider trading is most pronounced for options with a low theoretical value, for instance options with low implied volatility and short time to maturity.
4. *Synthetic options:* Synthetic call options enable investors to substantially reduce the effects of market frictions. An OTM synthetic call consists of a position in the underlying asset and an ITM put. Given that the theoretical value of any ITM option is high, relative bid-ask spreads are low. Synthetic calls then enable the informed investor to obtain higher leverage. Trading synthetic options requires an investor to partly finance his positions by borrowing at the risk free rate and is thus likely restricted to sophisticated investors.

(B) Predictions related to the precision of the return signal (σ_κ):

1. *Impact on trading parameters:* Higher uncertainty about the announcement return will generally make

an investor more cautious and move closer ITM to ensure that the option is ITM following the announcement. However, this effect is relatively small, as insiders do not trade DOTM options anyway, especially when buying short term options. Overall, changes in the uncertainty about the announcement return have a limited effect on the behavior of insiders. In most instances, even substantial increases in this uncertainty only demand relatively small adjustments to trading parameters.

2. *Impact on expected returns:* Uncertainty about the announcement return uncertainty adds to the volatility of the underlying and thus increases the expected return of a trading strategy with positive vega, rather than decreasing it.[28]

(C) Predictions related to the expected announcement return (κ):

1. *Impact on trading parameters:* In most instances, insiders will trade further OTM when anticipating announcement returns of a higher magnitude. However, this shift to OTM trading is limited by market frictions. The sign of the anticipated return determines whether investors trade a (synthetic) call option (positive return), a put option (negative return), or a straddle (sign of return unkown).

2. *Impact on expected returns:* Generally, the higher the magnitude of the expected announcement return, the higher the expected returns to insider trading. Insiders can achieve significant returns even for zero κ.

(D) Predictions related to the precision of the timing signal ($\sigma_{\Delta t}$):

1. *Impact on trading parameters:* All else equal, higher event date uncertainty implies that informed investors will trade in longer maturity options to avoid purchasing options that expire worthless.

2. *Impact on expected returns:*

   All else equal, this need to trade in options with a longer maturity increases the initial price to set up any trading strategy with a negative option theta (all that are considered in this paper). This implies

[28] This effect is analogous to the increase in the Merton (1974) value of equity as a call option due to added noise in earnings information, formalized by Johnson (2004).

a reduction in the attainable leverage, and thus expected returns to insider trading. In fact, precision in the timing signal enabling trading briefly ahead of the event is one of the most important drivers of expected returns, especially for unscheduled events ahead of which there is no run-up in option prices and bid-ask spread due to increased speculation.

For scheduled events, prices and bid ask spreads will increase ahead of the event due to uninformed speculation. This can substantially reduce attainable returns.

(E) Predictions related to the expected timing (Δt)

1. *Impact on trading parameters:* The longer the period between the time an insider trades and the time of the anticipated announcement, the longer the maturity of the options an insider needs to trade to avoid that they expire worthless.
2. *Impact on expected returns:* All else equal, the need to trade in longer term options decreases expected returns to insider trading, as in H4b.

The results of our numerical analysis show that the relation between the determinants of informed trading (including the parameters defining the private signal, as well as pricing parameters such as the volatility of the underlying) and the set of trading parameters chosen by the insider is non-monotone and highly nonlinear. A significant part of the implications of our framework can thus not be reduced to simple hypotheses. For instance, the timing signal can heavily affect the insider's choice of moneyness, which is not captured by the above predictions.

B. Jump classification

One of multiple criteria used in our definition of an EPM is the prevalence of a jump as defined by Lee and Mykland (2008). We compute the statistic £$_i$ as the ratio of the (continuous) stock price return to the instantaneous volatility:

$$\mathcal{L}_t = \frac{R_t}{\hat{\sigma}_t} \tag{5}$$

where volatility is the realized bipower variation:

$$\hat{\sigma}_t^2 = \frac{1}{K-2} \sum_{j=t-k+2}^{t-1} \left|R_j\right| * \left|R_{j-1}\right| \tag{6}$$

Assuming that the drift and diffusion coefficients of the stochastic process describing the stock price do not vary a lot when Δt (the increment) approaches zero, the authors derive the limiting distribution of the maximums:

$$\frac{\max_{t \in \bar{A}_n} |\mathcal{L}_t| - C_n}{S_n} \longrightarrow \xi \tag{7}$$

where ξ has a cumulative distribution function $P(\xi \leq x) = \exp(-\exp(-x))$ and:

$$C_n = \frac{\sqrt{2\log(n)}}{c} - \frac{\log(\pi) + \log(\log(n))}{2c\sqrt{2\log(n)}} \tag{8}$$

$$S_n = \frac{1}{c\sqrt{2\log(n)}} \tag{9}$$

$$c = \sqrt{\frac{2}{\pi}}. \tag{10}$$

n stands for the number of observations. $\bar{A_n}$ is the time series indexes such as there is no jump between two consecutive time points.

While Lee and Mykland show that misclassification rates decrease in data frequency it can also be applied to daily data.[29] Following Lee and Mykland's recommendation, we set $K = 16$ to compute the statistics $\mathcal{L}_t$ from daily returns.

As in their study, we use a significance level of 5%. The threshold is hence equal to $-\log(-\log(0.95)) \approx 2.97$ For each stock, we obtain a time series of $\mathcal{L}_t$. If $|\mathcal{L}_t|$ exceeds $2.97 * S_n + C_n$, the return is classified as a jump.

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[29] For example, see Cremers et al. (2014).

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